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Neural Network Based Decision Support Model for Optimal Reservoir Operation

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Abstract. A decision support model (DSM) has been developed using the artificial neural networks (ANN) for optimal operation of a reservoir in south India. The DSM developed is a combination of a rule based expert system and ANN models, which are trained using the results from deterministic single reservoir optimisation algorithm. The developed DSM is also flexible to use multiple linear regression equations instead of trained neural network models for different time periods. A new approach is tried with the DSM based on trained neural network models, which use real time data of previous time periods for deciding operating policies. The developed DSM based on ANN outperforms the regression based approach.

Key words: decision support system, dynamic programming, neural network, optimization, reservoir operation

Notation

a, b, c, d, e	= Coefficients used in multiple linear regression
D_t	= Irrigation demand during time period t
e_t	= evaporation rate during time period t
E_t	= Evaporation during time period t
I_t	= Inflow during time period t
K	= Storage capacity of the reservoir
p	= number of patterns
q	= number of neurons in output layer
R_t	= Release during time period t
s	= sweep number
S_t	= Storage at the beginning of time period t
T	= number of fortnights
Z	= Objective function
y_j	= output from the neuron
y_{jt}	= target output value

1. Introduction

Optimal use of scarce water resources is the prime objective in drought prone areas. Water resources development projects are vital for the country like India where a high population density demands basic food and fiber requirements. Indian agriculture has been exposed to the vagaries of flood and drought. Recently, the emphasis has been shifted to efficient management of the water potential already created rather than constructing new storage structures due to non-availability of suitable sites for reservoirs, high initial investment cost and ecological and environmental disturbances. The present study is attempted to develop a DSM with the aid of ANN model for deriving operating rules for different time periods in an irrigation reservoir for the optimal use of available water resources.

1.1. LITERATURE REVIEW

Recently the ANN have been successfully applied in many water resources problems. ANN is a mathematical model mimicking the function of human brain. These models have two of the brain's important characteristics: a parallel and distributed architecture and an ability to learn. The ANN consists of neurons, which are activation functions arranged in different layers. In the feed forward type of the ANNs informations are transmitted in serial operations from one layer to another. The ANN model can be trained by either supervised or unsupervised learning methods. The knowledge is stored in the form of inter-connecting weights between subsequent layers after training (Rumelhart and McClelland, 1987). Recently neural network models are successfully applied for river stage forecasting, rainfall forecasting, groundwater flow remediation, for deriving operating policies of a reservoir, etc. (Cancelliere *et al.*, 2002; Chandramouli and Raman, 2001; French *et al.*, 1992; Hsu *et al.*, 1995; Karunanithi *et al.*, 1994; Raman and Chandramouli, 1996; Rogers and Dowla 1994; Saad *et al.*, 1994).

Elshorbagy *et al.* (2000) discussed the advantages and disadvantages of the ANN, linear and non-linear regression procedures in rainfall – runoff modeling. Jain *et al.* (1999) applied the ANN for reservoir inflow prediction and operation for a multi-purpose system. Liong *et al.* (2000) demonstrated the use of the ANN for river stage forecasting in Bangladesh and showed the improved results. Liong *et al.* (2000) used a multi-layered feed forward neural network model that was trained using supervised back-propagation learning. Zhang and Govindaraju (2000) used a modular neural network for predicting the watershed runoff using Bayesian concept. Philbrick, Jr. and Kitanidis (1999) discussed about the limitations of the deterministic optimization applied to reservoir operations and discussed about them using contrasting control policies developed using deterministic optimization of inflow forecasts and control policies using stochastic optimization of probabilistic inflows.

2. Problem Formulation

Practical real time operations require the specification of reservoir rules. Young, Jr. (1967) first initiated to derive rules using simple linear regression or multiple linear regressions from the deterministic optimization results. He derived regression equations using inflows and storages to find optimal releases. The general operating rule derived by the procedure suggested by Young, Jr. (1967) could capture some of the optimal solution resulting from the large deterministic optimization results. Yeh (1985) reviewed the reservoir management and operation models including simulation models. Linear programming (LP), dynamic programming (DP), non-linear programming (NLP) and simulation models and their applications in reservoir operation had been covered in an elaborate manner by this review. Yeh (1985) reviewed the advantages of DP for reservoir operation problems.

Bhaskar and Whitlach (1980) analysed a single multi-purpose reservoir using backward DP algorithm to obtain optimal results. They made use of the procedure of deriving general operating policies from deterministic optimization as initiated by Young (1967).

They also considered a quadratic loss function and derived monthly policies by regressing optimal set of releases on the input and state variables. Karamouz and Houck (1982) also developed a general reservoir system operating rules by deterministic optimization and constructed a dynamic programming – regression (DPR) model. The DPR model algorithm suggested by Karamouz and Houck (1982) had a deterministic dynamic program with a regression analysis.

Raman and Chandramouli (1996) developed a dynamic programming – neural network (DPN) model, which used neural network for deriving general operating policies from the deterministic dynamic programming optimization algorithm. They also compared the results to regression based models and showed that the DPN model gives improved performance than DPR model, stochastic dynamic programming model and standard operating policy.

The developed DSM has a deterministic DP module to perform the optimization. The results of DP are printed in the form of patterns and segregated to each time period. Neural network models are developed for different time periods. The DSM also has a set of rule base. The DSM takes the information about the time period and fires the neural network model trained for that particular time period (Figure 1). ANN model estimates the optimal release from the reservoir for the considered time period. The decision support developed is examined using case studies. For this purpose, two reservoirs namely Aliyar reservoir and Thirumurthi reservoir in the state of Tamil Nadu, India are considered. The historical fortnightly data for the Aliyar reservoir is available for 27 years (from 1970 to 1996). Aliyar reservoir (FRL + 320.000 m) is constructed at the foot hills in eastern slope of Anamalai hill range across Aliyar river with a storage capacity of 109 Mm^3. This river, a tributary to Bharadhapuza river system, originates from northern slopes of Anamalai Hills and flows in a north-westerly direction for about 22.4 km before it enters the plain. For the Aliyar reservoir, out of the 27 years, 20 years of data (1970–1989) are used for model construction and 7 years of

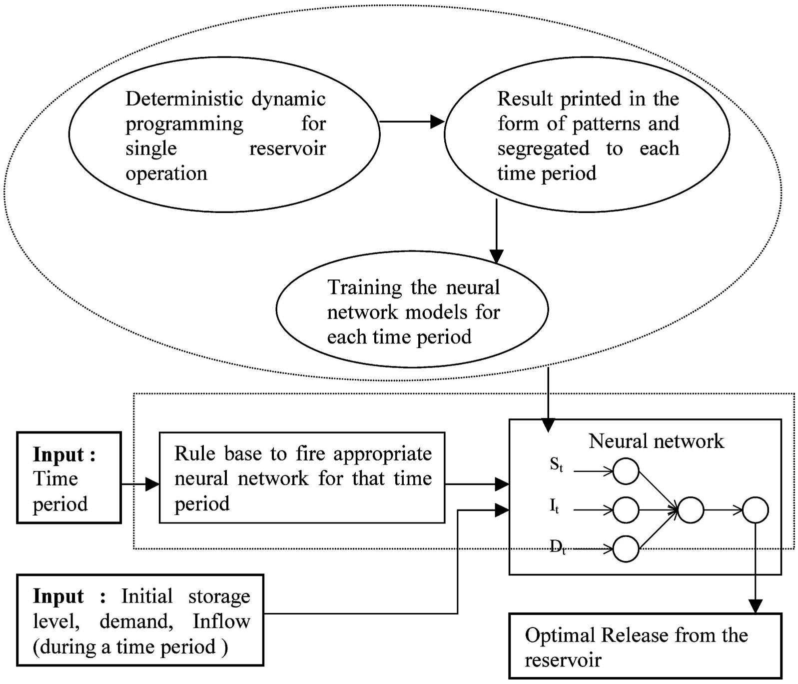

Figure 1. Developed decision support model 1 for reservoir operation.

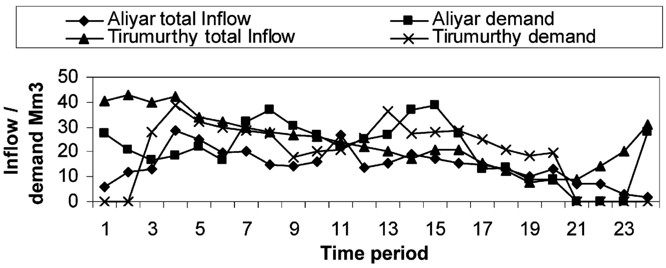

Figure 2. Fortnightly demands for Aliyar and Tirumurthi reservoirs – Average inflow and demand pattern.

data (1989–1996) are used for validation of the developed DSM. Thirumurthy reservoir is also located on eastern side of Anamalai hills across another river called Palar, a tributary to Bharadhapuza river system. It has a storage capacity of 52 Mm^3. Average fortnightly demands and average total inflows to these two reservoirs are given in Figure 2. For Tirumurthi reservoir the data are available for 23 years (from 1970 to 1996). Out of the 23 years, 20 years (from 1970 to 1993) of data are used for model construction and 3 years of data for model verification.

2.1. DECISION SUPPORT MODEL – DESCRIPTION

The considered DP algorithm is a fortnightly model and minimizes the squared deficit in the following objective function

$$\text{minimize } Z_t = \sum_{t=1}^{20\times 24} (D_t - R_t)^2 \tag{1}$$

where, D_t = Demand during time period t; and R_t = Release during time period t.

In the DP algorithm, initial storage volume of the reservoir is used as the state variable. The decision variable considered is the optimal release from the reservoir. The recursive relation for the deterministic DP model for any time period t is given by the equation

$$\begin{aligned} f_t^n(S_t) = \min R_t\big[Z_t + f_{t+1}^{n-1}(S_t + I_t - E_t - R_t)\big] \\ 0.0 \le R_t \le R_{t\max} \\ R_t \le S_t + I_t - E_t \\ R_t \ge S_t + I_t - K - E_t \\ S_{t\min} \le S_t \le S_{t\max} \\ E_t = f(S_t, S_{t-1}, e_t) \end{aligned} \tag{2}$$

where, $Z_t = (D_t - R_t)^2$; S_t = Storage at the beginning of time period t; I_t = Inflow during time period t; K = Storage capacity of the reservoir; E_t = Evaporation during time period t; e_t = Evaporation rate during time period t; and n = Total number of periods remaining before reservoir operation terminates.

The maximum and minimum storage constraints as well as the evaporation loss components are included in the formulation of the DP algorithm. The mass balance and continuity equations form the base of the recursive equation. Release and spills are treated with equal weights. The deterministic DP formulation can be solved generally by considering the average inflow or the actual inflow (Loucks *et al.*, 1981) in the field, since in this case inflow is considered to be a known quantity. The results of the optimization model are printed in the form of patterns. Raman and Chandramouli (1996) used a single neural network model and trained the ANN using the patterns generated from the optimization results.

2.2. DSM1 MODEL

In this work, the patterns are segregated for different time periods and for each time period, an ANN is trained (Figure 3). To fire the appropriate ANN, a rule base is created in the developed DSM1. For the reservoirs considered for the case study, three time periods (April 1st, 2nd and May 1st fortnights) have zero demand. Since no release is needed from the reservoir during these three time periods, no ANN

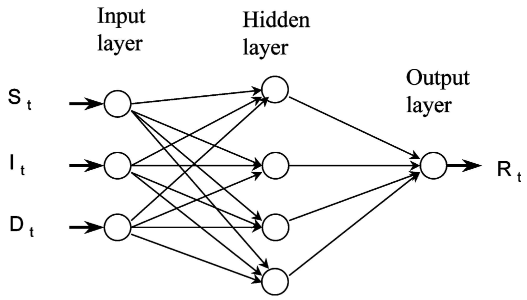

Figure 3. Neural network model for the DPN, DSM1 and DSM2.

models are developed. A simulation model is used for assessing the performance of different DSMs.

2.3. DSM2 MODEL

Further, DSM2 is also developed for examining the improvement in the performance by segregating the patterns by considering both time periods and storage levels i.e. two ANNs are trained for each time period, one for the storage above 50% of the total capacity and another less than 50% of the total capacity.

2.4. DSM3 MODEL

Another decision support system (DSM3) is developed to examine the ability of ANN to make use of previous time period data instead of the current time period. The deterministic optimization using regression and neural network methods attempt to capture the relationship between inputs and outputs. When the outputs are the control decisions and inputs are the state variables of the system, the problem is ill posed as control decisions are based on policies that are not known in advance.

Karamouz and Houck (1982) suggested the DPR model in which the inflow during that period is used as an input for obtaining the optimal release for that particular time period. They used a deterministic formulation. By considering the recommendations of Bhaskar and Whitlach (1980), Karamouz and Houck (1982) used a multiple linear regression form to express the optimal release R_t using initial storage S_t and inflow during the period I_t.

$$R_t = aI_t + bS_t + c \tag{3}$$

where a, b, and c = regression coefficients. The DPR model developed by Raman and Chandramouli (1996) is based on a multiple linear regression form

$$R_t = aI_t + bS_t + cD_t + d \tag{4}$$

In these models, both the DPR and DPN models, use the variable inflow I_t during a time period as a known quantity since it is a deterministic optimization.

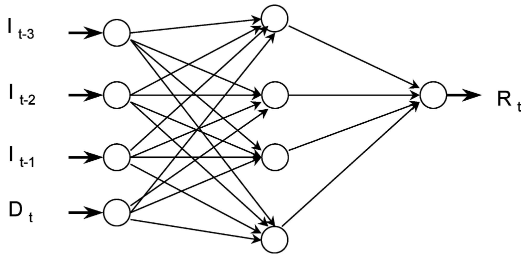

Figure 4. Neural network model for DSM3.

An attempt is made to develop operating policies, which needs the known data of previous time periods as input to decide about the decision variable. For this purpose, in the case of DSM3, the rule base is made to fire the ANN by considering a particular time period and the storage available at the beginning of the time period (i.e. similar to DSM2).

The initial storage that is the state variable is not included as the input variable in the operating policy since patterns are classified according to storage levels. For the DSM3 the neural network model is developed by considering demand during that time period and the inflow from the catchment during time periods $t - 3$, $t - 2$ and $t - 1$ (Figure 4) instead of the ANN shown in Figure 3 (which is used in DSM1, DSM2 and DPN models). Hence from the deterministic optimization results, the DSM3 develops operation rules based on the inflow from previous three time periods and demand during the time period *t*, which can be estimated in advance. Hence the problem is not ill posed as in the case of DPN, DPR, DSM1 and DSM2 models. For DSM1, DSM2 and DSM3 models, two approaches namely, one based on ANN and another based on regression are developed and examined in this study.

3. Aliyar Reservoir: Results and Discussions

The DSM is developed with flexibility to use the ANN or multiple linear regression. The results of six different models (DPN, DPR, DSM1 based on neural network, DSM1 based on regression, DSM2 based on neural network, DSM2 based on regression) are compared based on their performance for 7-year (1990–1996) verification series for Aliyar reservoir using a simulation model.

Further, model development results are also used for assessing the goodness of fit of a particular model. The two indices namely mean square error (m.s.e.) and mean relative error (m.r.e.) are used for assessing the fitness of a particular model. They are defined as follows:
Mean Square error (m.s.e.)

$$\text{mse} = \frac{1}{pq} \sum_{q} \sum_{j=1}^{p} \left(y_j^{(t)} - y_j\right)^2 \tag{5}$$

Mean Relative error (m.r.e.)

$$\text{mre} = \frac{1}{pq} \sum_{q} \sum_{j=1}^{p} \left| \frac{\left(y_j^{(t)} - y_j\right)}{y_j^{(t)}} \right| \times 100 \tag{6}$$

where, p = number of patterns used for training; q = number of nodes in the output layer; y_j^t = the target output pattern value (used for training) and y_j = output from neural network model. The m.s.e. and m.r.e. values indicate the goodness of fit for high and moderate output values respectively (Karunanithi *et al.*, 1994).

3.1. DECIDING THE ARCHITECTURE

Neural network modules for each fortnight are decided by analyzing different factors. Care had been taken in examining the number of neurons in each layer, single layered network, multi-layered network, normalizing the input patterns and learning rate. Different combinations starting with single neuron in the hidden layer are examined before deciding the optimal combination. The architecture of the neural network is decided by trial and error after examining different neurons in different layers.

The architecture is decided basically by examining the m.s.e. and m.r.e. values. A check is done to examine whether the m.s.e. and m.r.e. for the selected network pattern is less than the m.s.e. and m.r.e. values of the regression fits. Regression fits results are very useful for checking whether the considered combination of normalization factor and architecture is performing better for different patterns. In fact, the training is continued till there is improvement in the m.s.e. value and it is not terminated based on epoch counts.

Even though, the DSM is flexible to take different architecture for different fortnights, for this study, the architecture of the neural network is maintained as the same for different fortnights in a particular DSM to facilitate the training process in batches. The normalization factor is also assessed after performing different trials. Different combinations such as (1,100), (5,500), (120,180) etc. are tried before finalizing a combination [(1,100) refer that the input pattern sets are normalized by dividing them by 1 and output patterns are normalized by dividing them by 100]. By studying the nature of the pattern set, apart from sigmoidal activation function, clipped linear function is also examined while training using back-propagation algorithm.

3.2. MODEL CONSTRUCTION RESULTS: COMPARING DSM1 BASED ON ANN AND DSM1 BASED ON REGRESSION

The architecture of the neural network considered for different DSMs are given in Table I. The Figure 5 and Figure 6 show the m.r.e. and m.s.e. values of DSM1 based

Table I. The architecture of artificial neural network and normalization factors used for input and output patterns for different models

Model	Normalization factor	Architecture	Activation function
DPN model	(1000,500)	3-4-0-1	Sigmoidal
DSM1 trial 1	(120,180)	3-3-2-1	Sigmoidal
DSM1 trial 2	(5,500)	3-3-2-1	Sigmoidal
DSM2	(120,180)	3-3-2-1	Sigmoidal
DSM2 trial 2	(15,650)	3-3-2-1	Sigmoidal
DSM3 trial 1	(5,500)	4-3-2-1	Sigmoidal
DSM3 trial 2	(5,500)	13-3-2-1	Sigmoidal

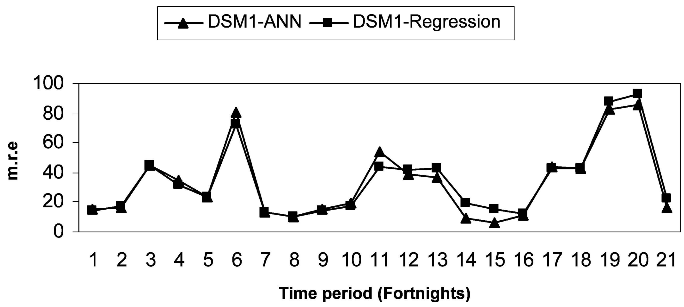

Figure 5. Comparing DSM1 based on ANN and regression (m.r.e. values).

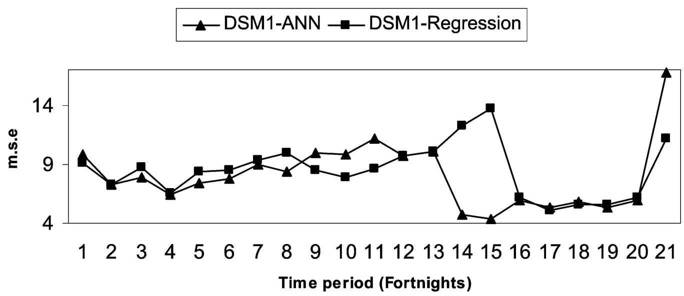

Figure 6. Comparing DSM1 based on ANN and regression (m.s.e. values).

on ANN and DSM1 based on regression respectively. The ANN gives marginal improvement over the regression. A normalizing factor of (120,180) is used in this analysis (Table I). The m.s.e. and m.r.e. indices are lower in some fortnights for ANN and some fortnights in regression (in the case of m.s.e. values, ANN is better in 12 time periods and in 9 fortnights, regression is better).

As trial 2, with normalization as (5,500), the model construction results showed a different trend (Figure 7). The output value range in a time period varies with respect to the maximum demand (in Mm^3) in that time period. For example, if we

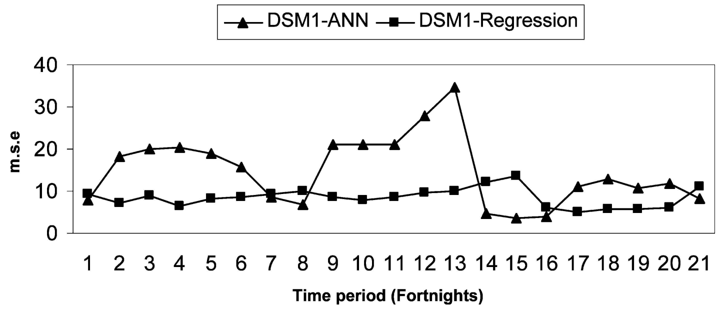

Figure 7. Comparing DSM1 based on ANN (trial 2) and regression (m.s.e. values).

consider time periods 19 and 20, the output patterns are in a range of 0–9 Mm^3 unlike the other time periods where it is in the range of 0–40 Mm^3. The ANN model based on (5,500) as the normalizing factor is not giving better results for other time periods 19 and 20. But for these two fortnights, (120,180) as the normalization factors gives better model output. Since the output range is very narrow for the time periods 19 and 20, a higher value for normalization (i.e. 5, 500) results in the clustering of the patterns in a very narrow space that leads to poor training using back-propagation algorithm. This also shows the segregation gives much better scope for training according to the pattern nature.

In the case of DSM1 based on ANN, the flexibility of choosing a better network architecture or normalization is available. As trial 3, the best results of trial 1 and trial 2 are considered for the DSM1 based on ANN (i.e. the time periods 1, 7, 8, 14, 15, 16, 24 from trial 2 and 2, 3, 4, 5, 6, 9, 10, 11, 12, 13, 17, 18, 19, 20, 21 from trial 1).

3.3. VALIDATION RESULTS

The validation of the developed models is done using a simulation model developed specifically for the reservoir system based on mass balance by incorporating the constraints. Seven years of fortnightly data are used for this purpose (Year 1989–1996). The simulation model uses the rules derived by the different DSMs according to user's choice for every fortnight. The model development is done in a deterministic environment i.e. the inflow during the time period is known. The initial storage at the beginning of a time period, inflow to the reservoir at every time period and the demand during that particular time period are given as input to the simulation model. The selected DSM that is linked to the simulation model will give the decision for the release during that time period.

The total inflow to the reservoir during the validation period (7 years) is 2430 Mm^3. The estimated demand to be met by the reservoir in the period of study is 3492 Mm^3. The results of the simulation runs based on different DSMs are given in Table II for the validation series. The best result of the simulation runs is

Table II. Validation and model development results for 7 years of data using simulation for Aliyar reservoir

Model	Squared deficit $(Mm^3)^2$	Spill (Mm^3)	Model	Squared deficit $(Mm^3)^2$	Spill (Mm^3)
DPN model	10718.21	86.24	DPR model	10907.32	96.84
DSM1 (based on ANN) (trial 1-normalizing (120–180)	10371.76	58.66	DSM1 (based on regression)	10675.11	69.15
DSM1 (based on ANN) (trial 2- normalizing (5–500))	12371.76	85.66			
DSM1 (based on ANN) (trial 3-by selected ANN normalization for different time periods)	10199.4	51.35			
DSM2 (based on ANN)	10480.10	70.35	DSM2 (based on regression)	10524.10	61.68
DSM3 (based on ANN)	11560.40	84.67	DSM3 (based on regression)	23209.09	313.09
DSM3 (based on ANN with previous 12 time period inflows and demand during that period)	13540.24	140.46			

from the DSM1 model based on ANN using trial 3 that uses different normalizations for different time periods. The improvement in the objective function shown over the proposed DPN model by DSM1 based on ANN using trial 3 is about 518.81. Further, in the trial 3, the spill amount reduces by 34.89 Mm^3 (Table II).

The demand of the reservoir during different time periods is shown in Figure 2. The release made by the DSM1 based on ANN, DPN models from simulation results are given in Figure 8. The release pattern of DSM1 based on ANN is more towards the inflow to the reservoir than the DPN model when the inflow is higher. Further when the inflow is less, the DPN and DSM1 based on ANN are very close. Due to this fact, the improvement in the performance of DSM1 is achieved with a lesser spill than DPN model. Figure 9 presents the squared deficit in each fortnight for the verification series for both the models. DSM1 is better performing than the DPN model. Figure 10 shows the better performance of the DSM1 based on ANN over DPN in the reservoir operation. In particular, during scarce years, the objective function value of DSM1 based on ANN is lesser than the DPN model.

In the case of trial 1, DSM1 based on ANN gives better results than DSM1 based on regression (Table II). But the model building results (m.r.e. or m.s.e. values) for

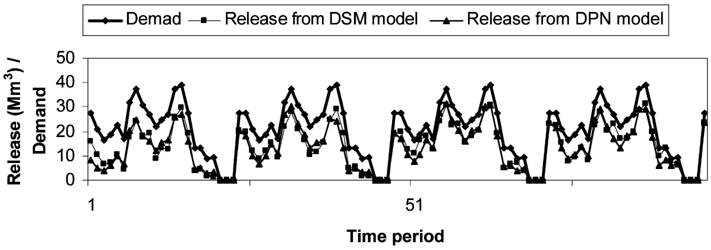

Figure 8. Releases from DSM1 based on ANN (trial 3) and DPN model.

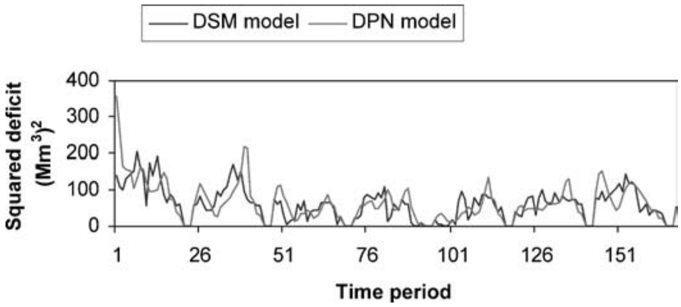

Figure 9. Squared deficit in each fortnight by DSM1 based on ANN (trial 3) and DPN model.

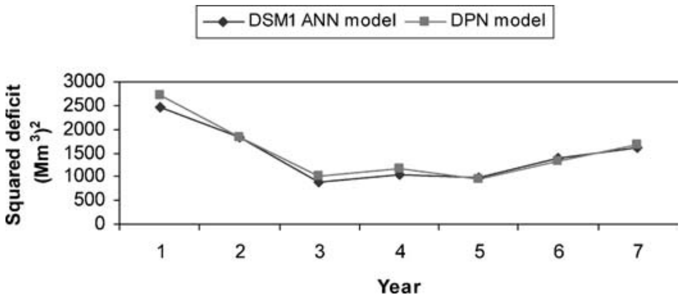

Figure 10. Comparing the performances of DSM1 based on ANN (trial 3) and DPN model.

some fortnights for ANN are higher than the regression indices. Even though the m.s.e. and m.r.e. indices are close for most of the time periods, the DSM1 based on regression does more hedging then DSM1 based on ANN in general. The spill also indicates this fact (Table II).

The m.s.e. results of another trial (trial 2) for DSM1 based on ANN and regression with normalization (5,500) is shown in Figure 7. In most of the time periods, the regression gives better results in the model development. The validation series results for the trial 2 are shown in Table II. DSM1 based on regression gives better performance than DSM1 based on ANN for trial 2. This indicates that the objective function value for DSM1 based on ANN is influenced if the neural network is not trained properly.

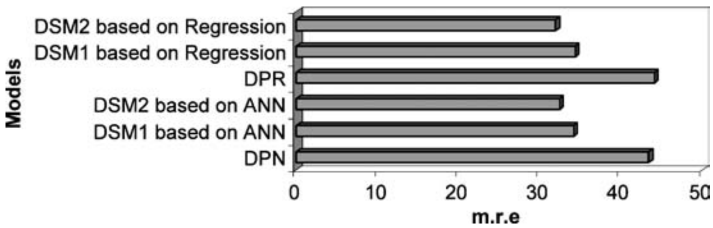

Figure 11. Comparing the m.r.e. values of DPN (DPR), DSM1 and DSM2.

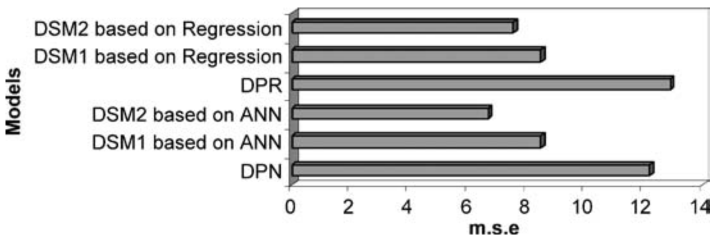

Figure 12. Comparing the m.s.e. values of DPN (DPR), DSM1 and DSM2.

The indices m.r.e. and m.s.e. are compared for DPN, DPR, DSM1 and DSM2 in Figure 11 and Figure 12 respectively. Average m.s.e. and m.r.e. values for different time periods are given for DPN, DSM1 and DSM2. In the case of segregation, the number of patterns resulting for training becomes less in number and training becomes much easier than the DPN model. Further, by choosing appropriate network architecture by studying the nature of the pattern for different fortnights, better training is achievable. Similarly, the segregation of patterns also gives better regression fits.

3.4. COMPARING DSM1 AND DSM2

From Figure 11 and Figure 12 it can be inferred that the model building results of DSM2 based on ANN are better than the DSM1 based on ANN. It is interesting to note that the reservoir operation performance of DSM2 based on ANN is not better than the DSM1 based on ANN when we consider the validation series results (Table II). Unexpectedly, even after repeated trials with different normalization and combinations of normalizations for different fortnights, the performance of DSM2 is not improving. It indicates that the segregation based on time period is more influencing the results rather than based on both time periods and storages. This also indicates that even though by segregation, the results of the model based on m.s.e. and m.r.e. improves, it does not influence in getting better results in reservoir operation. But the performance of the DSM2 based on ANN is better than DPN model by considering both model development and validation results.

From the performance of validation series and model building indices, it can be inferred that there is an improvement in the results with every additional segregation in the case of regression based models. Interestingly, DSM1 based on regression results are better than the DPN model results. When we have the regression based on deterministic operation policies, the performance of DSM based on ANN and regression at different segregation levels is always comparable.

3.5. DISCUSSIONS ON DSM3

While considering DSM3, which derives rules based on previous time period inflows, the ANN outperforms linear regression. The multiple linear regression used for different time period in this case is of the following form

$$R_t = a\, I_{t-3} + b\, I_{t-2} + c\, I_{t-1} + d\, D_t + e \tag{7}$$

It is interesting to note that the model development results for DSM3 based on ANN and regression (m.s.e.) (Figure 13) are very close. But when the regression fits are used in the validation series, results are encouraging only for DSM3 based on ANN. It outperforms DSM3 based on regression. This is due to the fact that the better non-linear mapping of the relationship exists between the input and output data by DSM3 based on ANN. The DSM3 based on regression performs poorly in all the time periods. (Figure 14) The operating policies of the DSM3 based on regression, fails to give optimal water allocation even when the sufficient storage is available in the reservoir and spills 313 Mm^3 whereas DSM3 based on ANN spills 84.67 Mm^3 (Figure 14). The linear regression coefficients with r^2 values for different fortnights are given in the Table III. It can be noted that the regression fit is having very low r^2 values and is highly influenced by the constant factor.

It is interesting that the DSM1 based on ANN and regression results are comparable and the improvement is marginal, whereas in the case of DSM3 based on ANN outperforms the DSM3 based on regression. It shows the deterministic nature of the model influences the regression based DSM. But ANN can manage better based on previous time period flow (i.e even though the inflow input is not deterministic). This nature is very useful for real time operation.

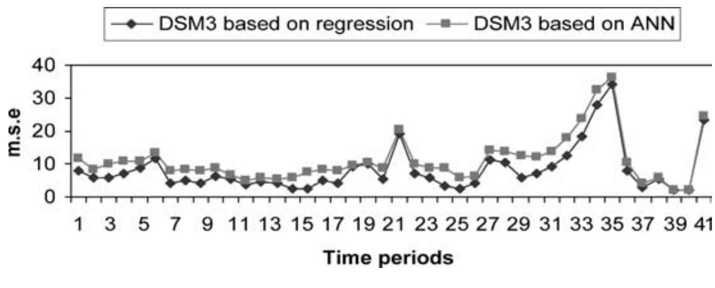

Figure 13. Comparing DSM3 based on ANN and regression (m.s.e. values).

Table III. Multiple linear regression fit for different time periods

Time	Storage level more than 50% of the total capacity						Storage level less than 50% of the total capacity					
period	*a*	*b*	*c*	*d*	*e*	R^2	*a*	*b*	*c*	*d*	*e*	R^2
1	0.3976	0.2094	−0.0753	0.1377	10.4788	0.092	0.0537	0.3480	−0.1379	0.0540	13.274	0.115
2	−0.0500	0.1352	−0.0276	−0.0232	16.7078	0.126	0.4500	0.1561	−0.0692	−0.1488	1.905	0.131
3	0.1414	0.1310	0.0074	−0.0864	8.9157	0.123	0.1134	0.0804	−0.0079	−0.1466	5.522	0.075
4	−0.0759	0.1457	0.0108	−0.0662	13.3068	0.243	−0.5066	0.0491	−0.0429	−0.0460	18.982	0.082
5	0.2660	0.1667	−0.0030	−0.0600	7.9072	0.367	0.2837	0.1335	−0.0351	−0.0919	4.613	0.45
6	0.1045	0.1475	0.0223	0.0044	4.3087	0.111	0.1683	−0.0430	0.0688	−0.0647	3.343	0.19
7	0.3760	0.0638	−0.0846	0.0585	10.5920	0.067	−0.0706	0.3121	−0.1864	0.0998	17.724	0.175
8	0.0783	0.1934	−0.1660	0.0221	24.4370	0.216	1.0319	0.2998	−0.1308	−0.0068	−18.033	0.33
9	0.0357	0.1843	−0.0060	−0.0997	19.7178	0.232	0.2119	0.1451	0.0443	−0.1159	9.557	0.179
10	0.3253	0.2065	−0.0092	−0.0283	7.9400	0.239	0.1106	0.2395	−0.0402	0.0231	7.589	0.256
11	0.1168	0.1925	−0.0249	−0.0160	9.3113	0.364	−0.0595	0.1892	0.0681	−0.0163	6.563	0.24
12	−0.0830	0.1648	0.0438	−0.0242	15.8712	0.241	0.1354	0.2772	−0.0204	0.1243	1.321	0.2
13	0.2044	0.1129	0.0631	0.0255	10.0353	0.178	0.0462	0.2949	0.1539	−0.0318	4.239	0.22
14	0.8589	0.1508	−0.1166	0.0784	−3.7394	0.211	0.4692	0.4476	−0.0731	0.1008	−2.942	0.303
15	0.2429	0.1453	0.0196	−0.1224	22.5776	0.25	0.0661	0.4331	−0.0270	−0.0289	17.829	0.266
16	0.6849	0.1821	0.0052	−0.0362	2.3063	0.2	0.4162	0.2688	−0.0396	−0.0235	4.029	0.261
17	0.2384	0.3136	−0.0399	−0.0423	3.2905	0.26	0.0593	0.1817	0.0233	−0.0771	2.285	0.231
18	0.3493	0.2058	0.0886	−0.0301	2.5543	0.179	0.0166	0.0694	0.0879	−0.0217	3.089	0.105
19	0.0733	0.3975	−0.0359	0.0846	0.8352	0.202	0.0148	0.0256	−0.0062	0.0073	0.502	0.147
20	1.0765	0.1506	0.1489	0.0174	−6.9901	0.176	0.2343	−0.0141	−0.0451	0.0131	−1.179	0.169
24	0.9022	0.1327	0.0742	−0.2000	−3.8425	0.093	0.3367	0.4488	−0.0245	−0.0705	3.580	0.091

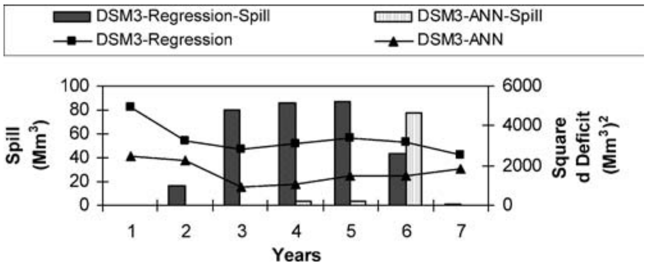

Figure 14. Validation results: Comparing DSM3 based on ANN and regression.

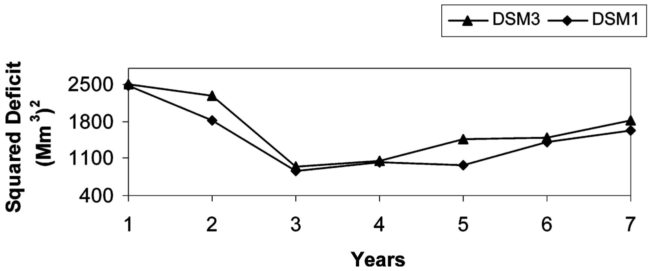

Figure 15. Validation results: Comparing the performance of DSM1 and DSM3 based on ANNs.

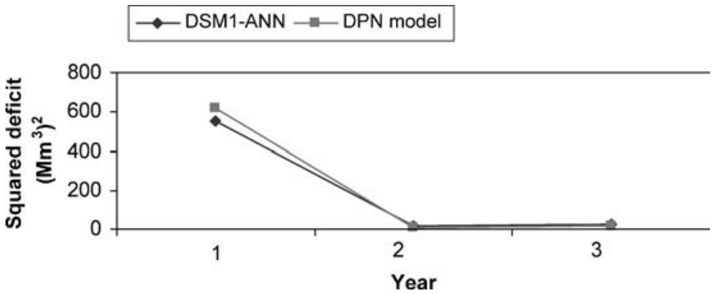

Figure 16. Verification results: DSM1 model and DPN model (Tirumurthi reservoir).

But the DSM1 based on ANN performs better than the DSM3 based on ANN (Figure 15). The DSM1 uses the inflow during the time period considered as a known quantity (since it is deterministic in nature). Since, DSM3 based on ANN uses the previous time period inflows, the neural network training manages both the flow prediction and optimization aspect together. Hence its performance suffers. The deterministic nature of DSM1 is the basic reason for the better result. Attempts are made by incorporating different combinations in input patterns in DSM3 (by including 12 previous monthly inflows and demands during the time period) but the results are not improving (Table II).

3.6. DISCUSSIONS ABOUT THE TIRUMURTHI RESERVOIR

Figure 16 presents the performance of DSM1 and DPN model results for the second reservoir for the validation series. DSM1 model gave marginal improvement over DPN model performance. For the Tirumurthi reservoir also very similar performance resulted with the DPN, DPR, DSM1, DSM2 and DSM3 models.

4. Conclusion

In this case study, the developed DSM based ANN in deriving the general reservoir operating policies based on segregation in different ways leads to improved performance of the system. Further segregation helps both ANN based and regression based models. The ANN based DSM which derives reservoir operating policies based on inflows of previous time periods outperforms regression method. Even though the performance of approach based on ANN with previous time periods inflow data is not better than ANN with deterministic inflow and initial storage, it is more suitable in the real field problems.

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References

Bhaskar, N. R. and Whitlach, E. E., Jr., 1980, 'Derivation of monthly reservoir release policies', *Water Resour. Res.* **16**(6), 987–993.

Cancelliere, A., Giuliano, G., Ancarani, A., and Rossi, G., 2002, 'A neural networks approach for deriving irrigation reservoir operating rules', *Water Resour. Manage.* **16**(1), 71–88.

Chandramouli, V. and Raman, H., 2001, 'Multi reservoir modeling with dynamic programming and neural network', *J. Water Resour. Plann. Manage. ASCE*, **127**(2), 89–98.

Elshorbagy, A., Simonovic, S. P., and Panu, U. S., 2000, 'Performance evaluation of artificial neural networks for runoff prediction', *J. Hydrol. Engg. ASCE*, **5**(4), 424–427.

French, M. N., Krajewski, W. F., and Cuykendal, R. R., 1992, 'Rainfall forecasting in space and time using a neural network', *J. Hydrol.* **137**, 1–37.

Hsu, K. L., Guptha, H. V., and Sorooshian, S., 1995, 'Artificial neural network modeling of the rainfall – runoff process', *Water Resour. Res.* **31**(10), 2517–2530.

Jain, S. K., Das, A., and Srivastava, D. K., 1999, 'Application of ANN for reservoir inlfow prediction and operation', *J. Water Resour. Plann. Manage. ASCE*, **125**(5), 263–271.

Karamouz, M. and Houck, H., 1982, 'Annual and monthly reservoir operating rules', *Water Resour. Res.* **18**(5), 1337–1344.

Karunanithi, N., Grenney, W. J., Whitley, D., and Bovee, K., 1994, 'Neural networks for river flow prediction', *J. Comp. Civil Engg. ASCE*, **8**(2), 201–220.

Liong, S. Y., Lim, W. H., and Paudyal, G. N., 2000, 'River stage forecasting in Bangladesh: Neural network approach', *J. Comp. Civil Engg. ASCE*, **14**(1), 1–8.

Loucks, D. P., Stedinger, J. R., and Haith, D. A., 1981, *Water Resources Systems Planning and Analysis*, Prentice-Hall, Englewood Cliffs, New Jersey.

Philbrick, C. R., Jr. and Kitanidis, P. K., 1999, 'Limitations of deterministic optimization applied to reservoir operations', *J. Water Resour. Plann. Manage. ASCE*, **125**(3), 135–142.

Raman, H. and Chandramouli, V., 1996, 'Deriving a general operating policy for reservoirs using neural network', *J. Water Resour. Plann. Manage. ASCE*, **122**(5), 342–347.

Rogers, L. L. and Dowla, F. V., 1994, 'Optimization of groundwater remediation using artificial neural networks with parallel solute transport modelling', *Water Resour. Res.* **30**(2), 457–481.

Rumelhart, D. E. and McClelland, J. L., 1987, Parallel Distributed Processing: Explorations in the Microstructure of Cognition, Vol. I and II, M.I.T. Press, Cambridge, MA.

Saad, M., Turgeon, A., Bigrs, P., and Duquette, R., 1994, 'Learning disaggregation technique for the operation of long-term hydro-electric power systems', *Water Resour. Res.* **30**(1), 3195–3202.

Yeh, W., 1985, 'Reservoir management and optimization models: A state of the art review', *Water Resour. Res.* **21**(12), 1797–1818.

Young, G. K. Jr., 1967, 'Finding reservoir operating rules', *J. Hydrau. Div. ASCE*, **93**(6), 297–321.

Zhang, B. and Govindaraju, R. S., 2000, 'Prediction of watershed runoff using Bayesian concepts and modular neural networks', *Water Resour. Res.* **36**(3), 753–762.