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Testing of catchment module of integrated reservoir-based canal irrigation model for kangsabati irrigation project

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Abstract

Bhadra, (2007) developed Integrated reservoir based canal irrigation model (IRCIM). It consist of catchment, reservoir, crop water demand modules. In this study, IRCIM was applied on Kangsabati irrigation project, West Bengal, India for period of 1998 to 2003. Runoff was predicted using two techniques namely, Distributed SCS Curve Number (CN) with Muskingum routing and Artificial Neural Network (ANN) Backpropogation techniques available in catchment module. Distributed SCS CN method requires subbasin information, land cover characteristics, overland and channel information and daily rainfall on subbasin, whereas ANN method requires daily rainfall and runoff values. Catchment module was calibrated and validated using performance criteria modelling efficiency (ME) and coefficient of residual mass (CRM). ANN technique of runoff prediction involves extensive training of the network, where the unpredictable correlation of rainfall and runoff is also been taken into consideration which is not possible for conceptual model such as SCS CN method. Thus, results showed that for Kangsabati reservoir catchment, runoff values, predicted using ANN result in better match with observed runoff values compared to semi-distributed conceptual SCS CN method.

Highlights

Runoff prediction by Empirical method ANN with Levenberg-Marquardt algorithm more accurate than Physical based distributed (GIS-based SCS CN method with muskingum routing)

Keywords: Integrated reservoir-based canal irrigation model, artificial neural network, levenberg-marquardt, SCS curve number.

In India, the distribution of water resources is highly uneven over both space and time. A fierce competition for water among the urban, industrial, agricultural and environmental users has begun. Although, there is increasing demand for food to feed the expanding population, less water is available for boosting the agricultural production. Further, investment constraints and environmental issues limit irrigation expansion, thus it is essential to improve the performance of the surface irrigation which operate at low overall efficiency of 33% (Kumar and Senseba, 2008). The land eventually irrigated is often less than planned and crop yields are not as high as expected. As a consequence, the irrigation sector has to become more efficient to produce more per unit of water. However, water management in major irrigation projects is a complex issue as it involves reservoir catchment, reservoir, canal network hydraulics and command area hydrology. The mathematical models can help in better decision making to operate irrigation project more efficiently.

A number of models have been developed by various researchers for runoff prediction using SCS method (Hawkins, 1993; Hamer *et al.,* 2007 and Qui *et al.,* 2014) with Muskingum routing technique (Gelegenis and Serrano, 2000) and by using back propagation artificial neural network (Jain *et al.,* 1999; Raghuwanshi *et al.,* 2006; Vivekanandan, 2011; Phukoetphim *et al.,* 2014 and Vafakhah *et al.,* 2014). Several models have been developed for reservoir operation (HEC, 1971; Tu *et al.,* 2003; Ganji *et al.,* 2007; Talukdar *et al.,* 2011 and Guo *et al.,* 2014), crop water demand calculation (Rowshon *et al.,* 2009; George *et al.,* 2011; Hlavinka *et al.,* 2011 and Sakaguchi *et al.,* 2014), and for canal flow simulation: Merkely (1995) reported a hydraulic simulation model CANALMAN (Canal Management) for unsteady flow simulation in branching canal networks. Shende *et al.* (2005) developed model for irrigation canal network with object oriented approach. The model solves the hydrostatic Saint Venant equations using an explicit Finite volume method with a Godunov-type high resolution shock capturing technique. Islam *et al.* (2008) developed a canal hydraulic simulation model 'CanalMod' that can simulate both steady flow and unsteady flow. Bautista *et al.* (2009) developed an unsteady flow hydraulic model WinSRFR for analyzing surface irrigation systems. The model was developed to analyze performance of irrigation events to formulate design and operational alternatives through simulation studies using an unsteady one-dimensional flow model. Lozano *et al.* (2012) used the unsteady state Simulation of Irrigation Canal (SIC) model to investigate the influence of roughness on the performance of an irrigation canal in Spain. These models work independently and interlinking them is quite a difficult task. It involves setup, calibration and validation of all the models separately and formatting of one model's output to use it as input to other model. The entire process becomes time consuming and tedious as one faces many difficulties like, repetitive data entry, different modelling approach, incompatible data format, varied time scale, etc. Over the years some attempts have been made to combine the hydraulic-hydrologic simulations of canal-command for efficient irrigation water management, one in Mahanadi Reservoir Irrigation Scheme (Singh *et al.,* 1997) and the other in Right Bank Main Canal (RBMC) of Kangsabati Irrigation Project, West Bengal (Mishra *et al.,* 2005). Both studies, however, did not take into account reservoir component. Rowshon *et al.* (2009) developed a Rice Irrigation Management Information System (RIMIS) for analyzing different scenarios of the water allocation with changes in canal inflows, rainfall, crop evapotranspiration and irrigation efficiency. Hajilal *et al.* (1998a and b) though incorporated a reservoir component in a similar study in Jayakwadi Irrigation Project, Maharashtra; they did not consider reservoir catchment hydrology. To overcome these limitations of the existing models, Bhadra *et al.* (2009a) developed an Integrated Reservoir Canal Irrigation Model (IRCIM) by integrating all the components (catchment, reservoir, canal and command) responsible for the efficient management of reservoir-based irrigation projects. The aim of the present study is to test the runoff prediction performance of the SCS curve number and ANN based techniques, which are available in the catchment module of the IRCIM. The present study is carried out for the Kangsabati irrigation project, West Bengal. Kangsabati irrigation project acts as the lifeline for the predominantly rice based agrarian economy of Bankura, Midnapore and Hoogly districts of West Bengal.

Study Area and Data

Kangsabati Irrigation Project, situated in the mid-western part of West Bengal. Kangsabati dam, built just above the confluence of Kangsabati and its tributary Kumari, is located at 22° 57′ 30″ N latitude and 86° 45′ 30″ E longitudes. Kangsabati reservoir supplies water to Right Bank Main Canal (RBMC) and Left Bank Feeder Canal (LBFC). Figure 1 shows both the catchment (3428 km^2) and command area (5568 km^2) of Kangsabati reservoir. The reservoir is designed to provide supplement irrigation of 250 mm depth over an area of 3,40,750 ha during kharif season and provision is also made for raising rabi crops over an area of 60,629 ha. Average annual rainfall of the catchment and command area is 1152 mm and 1400 mm, respectively. The design discharge at the head regulator of RBMC system, LBFC system and the spillway of the Kangsabati dam are 79.10, 199.55 and 6372 m^3/sec, respectively.

Daily rainfall data of six years (1998-2003) measured at five rain-guage stations in Kangsabati reservoir catchment, namely, Kangsabati Dam, Rangagora, Kharíduar, Tusama and Simulia were collected from Central Water Commission, Asansol, Ministry of Water Resources, Govt. of India. The toposheet of Kangsabati catchment, land use classification map and soil map were available in the Agricultural and Food Engineering Department, IIT Kharagpur, from previous study. General characteristic curves, such as stage-area curve, stage-volume curve of the Kangsabati reservoir; dead storage level; full storage level; daily flow releases at head regulators of RBMC and LBFC; spillway discharges as downstream flow from reservoir and daily inflow to the reservoir from the catchment were collected for the period of six years (1998-2003) from the Office of the Superintending Engineer, Irrigation and Waterways Department, Bankura, Govt. of West Bengal. In addition, canal network information was also collected. Seepage loss rate in the canal and value of field application efficiency were taken from the Water and Power Consultancy Services (India) Ltd. report (WAPCOS, 2003). Daily rainfall, pan evaporation, maximum temperature, minimum temperature, average relative humidity, sunshine hour and wind speed data of Susunia farm of Bankura, Jhargram and Kharagpur were collected for the same 6 years period (1998-2003) from the Department of Agriculture, Govt. of West Bengal. Kharif and rabi crop data were obtained from the Water and Power Consultancy Services (India) Ltd. report (WAPCOS, 2003).

In the Kangsabati irrigation project, a variable discharge, variable duration and variable frequency delivery scheduling is practiced. On an average, four irrigations are provided in each cropping season (kharif and rabi). Here, an irrigation represents canal water supply over 10 to 15 days, followed by an equal or longer duration of canal closure. The duration and frequency of irrigation are decided jointly by the official of Irrigation and Waterways Department and Agriculture Department, Government of West Bengal.

Brief Description of IRCIM

Detail description of the model is available in Bhadra *et al.* (2007). However, it is briefly described herein. The integrated reservoir-based canal irrigation model (IRCIM) has a modular structure and comprised catchment, reservoir and crop water demand modules. Either SCS CN or ANN method of catchment module can be used for prediction of inflows to reservoir on daily basis. The SCS curve number method with Muskingum routing technique can be used if rainfall, land use, soil, river network information are available and ANN technique can be used if rainfall and daily runoff data are available. The reservoir module is based on conservation of mass approach, and results in daily reservoir storage. Total storage in the reservoir is the storage corresponding to stage of the reservoir obtained from the stage-storage curve. Water balance equation was used for determining crop water demand of both paddy and field crops.

Crop water demand module requires climatic data of station, crop coefficient information sowing/transplanting and harvesting dates, soil moisture content information, saturated hydraulic conductivity and maximum possible discharge at the distributary head regulator to decide delivery scheduling. The irrigation management system controls and guides the data flow among different modules and decides optimum allocation of water at distributary head by a rotational distribution system. The canal flow model of Vyas and Sarma (1992) was modified and used in IRCIM to estimate the wetted area and seepage losses in canals, and the irrigation release requirement at the headwork of the main canal. For each distributary group, the canal flow model starts simulating at the downstream end distributary of the group and progresses sequentially upstream to the first distributary of that particular group. Then, the total irrigation requirement of that group is translated up to the reservoir through the main canal. The IRCIM also performs the postseason evaluation of the irrigation system, using performance indicators like adequacy, equity, and dependability.

The front end of the IRCIM was developed in Visual Basic 6.0 and the back end coding was done in C language. Required input files were created by VB and saved in a particular project folder. During run time, the required program (C executable) is called through *Shellexecute* function. The Graphical User Interface (GUI) is the most important feature of the model as it provides a better interaction between the model and its user. It is based on a mouse-driven approach with pop-up windows, pull-down menus and button controls. The reservoir and crop water demand modules can be operated independently or these can be simulated together under the irrigation management system.

Methodology

IRCIM consists of mainly three modules; namely, catchment, reservoir and crop water demand module. Irrigation management system is the core of IRCIM which control the operations among these three modules.

In the catchment module of IRCIM, runoff from reservoir catchment can be predicted by using either the SCS curve number (CN method, SCS 1967) combined with the Muskingum routing technique (Neitsch *et al.*, 2002) or the artificial neural network (ANN) technique using the Levenberg–Marquardt algorithm, depending on the data availability. Bhadra *et al.* (2009b) delineated sub-basins; and extracted basin and reach parameters from DEM of the Kangsabati catchment area. Those values were used as input to IRCIM to predict the runoff from the watershed using distributed curve number method. The catchment has five raingauge stations (Kangsabati Dam, Rangagora, Kharidwar, Tusama and Simulia) and the area corresponding to each station was determined using the Thiessen polygon method. The number of subbasins under each rain gauge was determined by overlaying the Thiessen polygon map over the delineated watershed map in a geographical information system (GIS) environment. Land use and soil type of each land cover of the subbasins were determined by overlaying the land use classification map and the soil map over the delineated watershed map.

To predict the runoff using the SCS CN technique, the model needs to be calibrated to determine correct combination of seven calibration parameters within the specified range. These calibration parameter are Manning's n for longest path in sub-basin (0.025 - 0.1); Manning's n for overland flow in sub-basin (0.01 - 0.4); Manning's n for reach (0.025 - 0.1); initial abstraction coefficient (0.1 - 0.3); weighting factor, X, for Muskingum routing (0 - 0.3) and Muskingum routing coefficients, $coef_1$ (0 - 1.5) and $coef_2$ (0 - 1.5). For calibration, rainfall-runoff data of three successive years (1998 - 2000) were used. The best combination was chosen on the basis of two performance indicators, namely, Modelling Efficiency (ME) and Coefficient of Residual mass (CRM). For the perfect model values of ME and CRM should be closer to 1 and 0, respectively. The validation was done for the period of three years (2001 - 2003) using average values of all seven calibrated parameters.

In ANN technique, most suitable network was selected by performing several trainings. The selection of training data that represents the characteristics of meteorological pattern is extremely important in modelling. The training data should be large enough to contain the characteristics of the catchment and to accommodate the requirements of the ANN architecture. In this study, minimum number of neurons in input layer was taken as five considering daily rainfall data from five different rain-gauge stations in the catchment. The networks were trained with varying number of input neurons (5, 10, 15, 20, 25 and 30) considering not only present but also up to past five days rainfall data of gauging stations for taking into account the effect of antecedent moisture content. Number of neuron in the output layer was always taken as one, representing outflow at the outlet point of the catchment (at Kangsabati reservoir site). The training was performed by changing either number of input neurons, or hidden neurons, or hidden layers for 5 simulation cycles to obtain the best network architecture. One of these three parameters was varied at a time while keeping others constant. The training process was terminated when one of the two criteria was fulfilled, i.e., either the error reduced below a given error tolerance (0.001-100.0) or the number of training cycles reached maximum limit. Subsequently, that best network was trained for different number (5, 10, 15 and 20) of training cycles to find out the optimum number of training cycles. The training of neural networks for rainfall-runoff modelling was performed for successive 3 years (1998-2000), whereas testing was performed for years 2001 to 2003, using the Levenberg-Marquardt algorithm technique.

Performance measures

Performance of catchment module is evaluated using two dimensionless statistical performance criteria viz., Modelling Efficiency (ME) and Coefficient of Residual Mass (CRM). The modeling efficiency (ME) is estimated using the following equation:

$$ME = \frac{\left[\sum_{i=1}^{n_d}\left(O_{v,i} - \overline{O}_v\right)^2 - \sum_{i=1}^{n_d}\left(P_{v,i} - O_{v,i}\right)^2\right]}{\sum_{i=1}^{n}\left(O_{v,i} - \overline{O}_v\right)^2} \tag{1}$$

Where, $P_{v,i}$ = predicted or simulated value; $O_{v,i}$ = observed value; $\overline{O}_v$ = average observed value and n_d = number of data used for evaluation.

Table 1. Calibration parameters for SCS CN method

Year	'n' for longest path of sub-basin	'n' for overland flow of sub-basin	n for reach	I_a	X	coef1	coef2
1998	0.075	0.01	0.05	0.2S	0.2	0.5	0.6
1999	0.075	0.01	0.05	0.2S	0.2	0.8	0.4
2000	0.075	0.01	0.05	0.3S	0.1	0.9	1.1

Table 2. Comparison among the networks for same number of cycles

Cases	Network	Number of hidden layer	Number of cycles	ME	CRM
1. Varying number of input neurons for same number of hidden neurons and hidden layers	5-20-1	1	5	0.27	0.12
	10-20-1	1	5	0.50	-0.13
	15-20-1	1	5	0.87	-0.01
	20-20-1	1	5	0.94	-0.05
	25-20-1	1	5	0.43	-0.56
	30-20-1	1	5	0.60	-0.52
2. Varying number of hidden neurons for same number of input neurons and hidden layers	20-5-1	1	5	0.12	0.09
	20-10-1	1	5	0.58	-0.41
	20-15-1	1	5	0.76	0.08
	20-20-1	1	5	0.94	-0.05
	20-25-1	1	5	0.58	-0.17
	20-30-1	1	5	0.93	-0.32
3. Varying hidden layers for same number of input and hidden neurons	20-20-1	1	5	0.94	-0.05
	20-20-20-1	2	5	0.30	-0.27

The coefficient of residual mass (CRM) is estimated using the following equation:

$$CRM = \frac{\left[\sum_{i=1}^{n_d} O_{v,i} - \sum_{i=1}^{n_d} P_{v,i}\right]}{\sum_{i=1}^{n_d} O_{v,i}} \qquad (2)$$

This criterion indicates the overall under- or over-estimation of the observed value. For a perfect model, the value of CRM is zero. A positive value of CRM indicates the tendency of the model to underestimate, whereas a negative value indicates a tendency to overestimate the observed data.

Results and Discussion

In SCS method, for all three calibration years, best results were obtained for Manning's n for longest path in sub-basin (N_{ch}) = 0.075; Manning's n for overland flow in sub-basin (N_{ov}) = 0.01; and Manning's n for reach (N_{rch}) = 0.05 (Table 1). These calibrated Manning's n values satisfactorily represented the existing characteristics of sub-basins and reaches of the study area. The values of other calibration parameters however varied from year to year. Figure 2 shows that predicted inflow is matching well with observed inflow in peak and off peak period for most of the calibration years (1998-2000). Using average calibrated values of all seven parameters, model was validated for years 2001, 2002 and 2003 (Figure 3). During validation, ME value is as high as 0.46 and CRM as low as 0.04, which are quite acceptable. However, all the positive CRM values indicate that the model is under-predicting runoff or reservoir inflow.

In ANN technique, Table 2 presents set of results for each of the three cases viz., varying either number of input neurons or hidden neurons or hidden layers while keeping other two parameters constant. The other two constant parameters in each of these three above cases were kept at their best-network value. The model performance improved with increase in input neurons (20) and number of hidden neurons (20) up to a limit and therefore after it varied. The network 20-20-1 (20 input neurons to consider past three days rainfall data in addition to present day rainfall data of five rain-gauge stations, and 20 hidden neurons in a single hidden layer) for 10 simulation cycles performed the best after training (Table 3). Time series plot of observed and predicted runoff for the calibration period of 1998 to 2000 using the selected network 20-20-1 is shown in Figure 4. It can be seen from the figure that there is a very good agreement between the observed and predicted runoffs for both peaks and off-peak periods. ANN module was validated for the monsoon season of years 2001, 2002, and 2003 (Figure 5). In the validation years, ME range from 0.61 to 0.78 and CRM from -0.07 to 0.24 as shown in Figure 5.

Table 3. Comparison among the networks for the different number of cycles

Network	Number of Cycles	ME	CRM
20-20-1	5	0.86	-0.107
20-20-1	10	0.98	0.012
20-20-1	15	0.98	-0.0013
20-20-1	20	0.98	0.0014

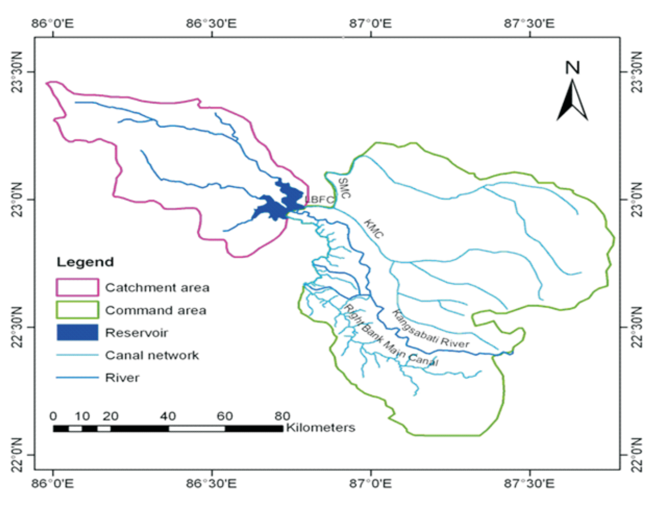

Figure 1. Catchment, reservoir and command area of Kangsabati irrigation project

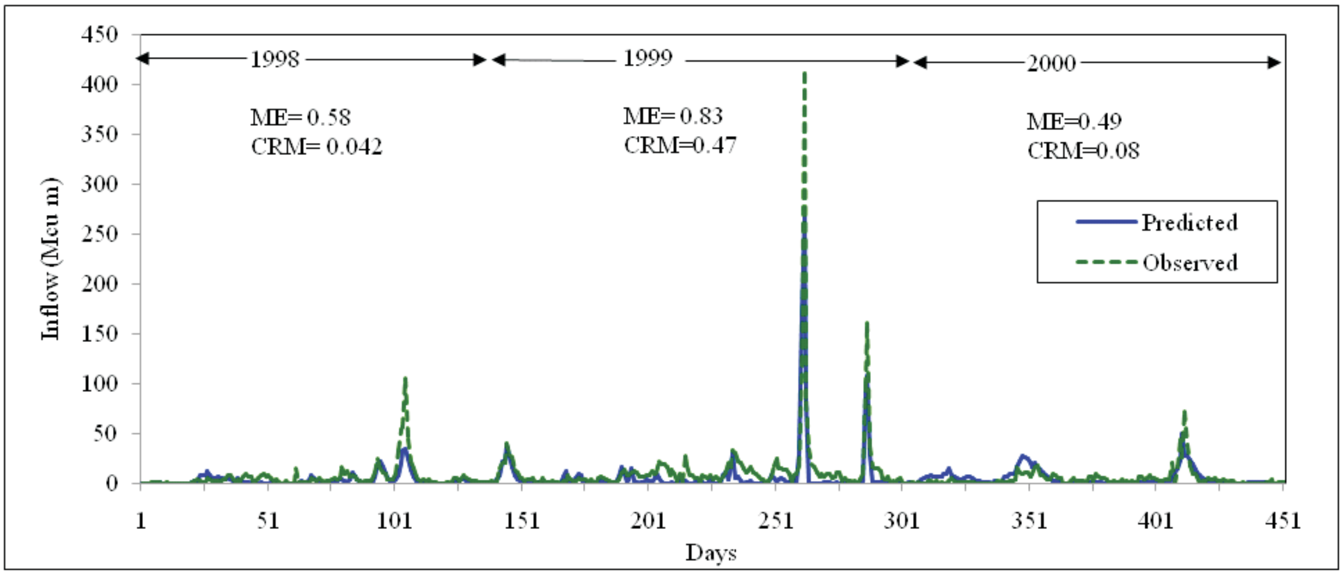

Figure 2. Time series plot for SCS CN method (calibration years 1998-2000)

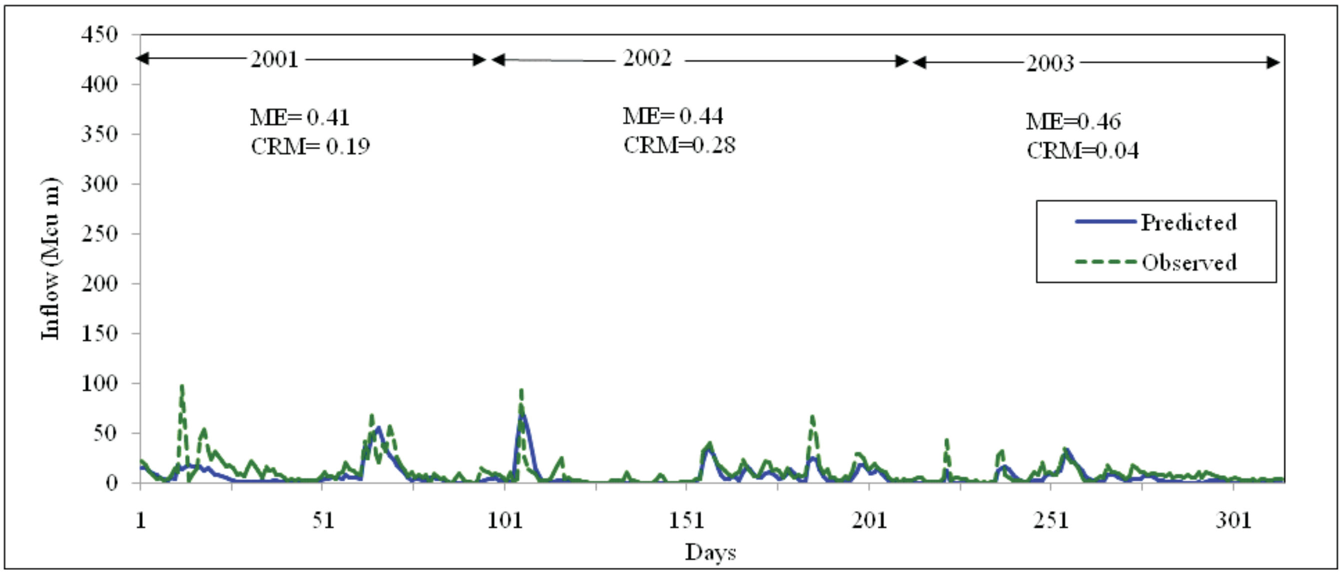

Figure 3. Time series plot for SCS CN method (validation years 2001-2003)

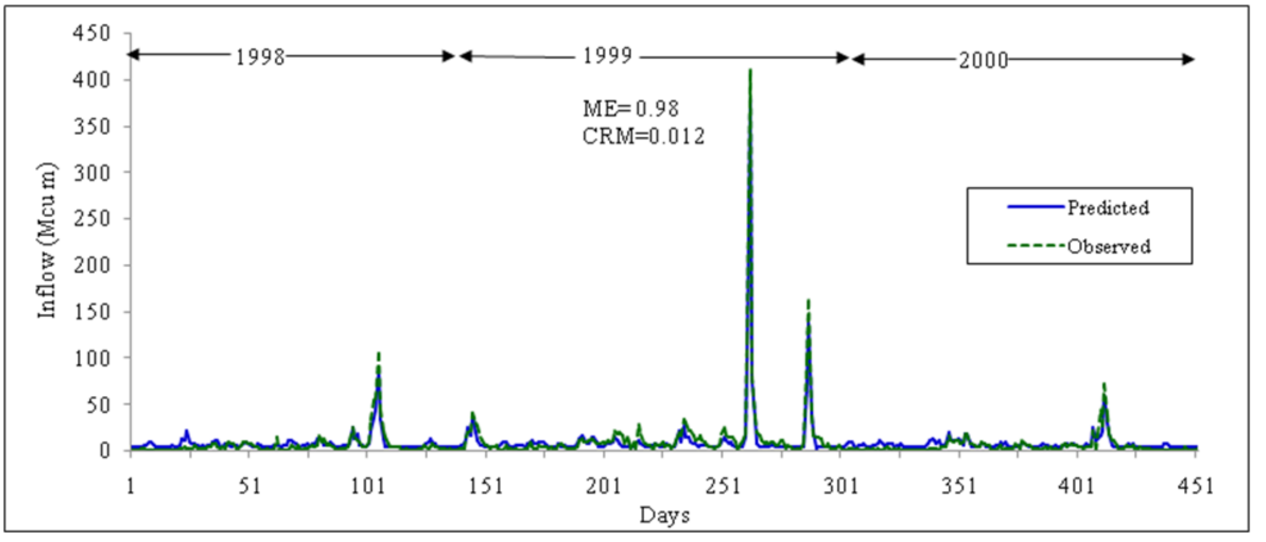

Figure 4. Time series plot for ANN technique (calibration Period - 1998 to 2000)

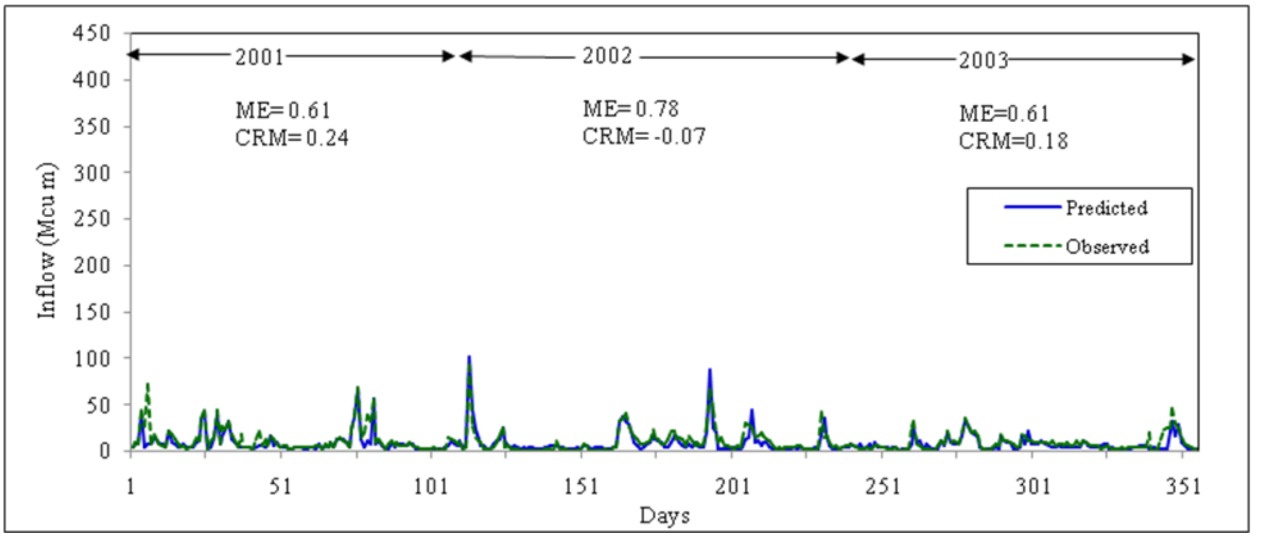

Figure 5. Time series plot for ANN technique (validation years 2001-2003)

From validation results, it is evident that ANN technique predicted daily runoff values more accurately compared to SCS CN method. Because, for the same length of rainfall-runoff dataset, ANN technique of runoff prediction involves extensive training of the network, where the unpredictable correlation of rainfall and runoff is also been taken into consideration which is not possible for conceptual model such as SCS CN method. Thus, runoff values, predicted using ANN model, resulted in better match with observed runoff values compared to the semi distributed conceptual SCS CN model.

Summary and Conclusion

In this study, an integrated reservoir based canal irrigation model was tested in Kangsabati irrigation project, West Bengal, India. The model consists of catchment module, reservoir module and crop water demand module. The rainfall-runoff modelling was performed using SCS curve number method combined with muskingum routing technique and ANN with Levenberg-Marquardt algorithm technique, included in catchment module. In case of more data requiring semi-distributed conceptual SCS CN model, all subbasin and channel parameters were successfully extracted using GIS techniques in a time and cost effective manner. For Kangsabati catchment, 0.075 as N_{ch}; 0.01 as N_{ov}; 0.05 as N_{rch}; 0.2 as I_a coef; 0.2 as X; 0.725 and 0.675 as coef1 and coef2, respectively, can be used as representative values for validation of the model in future studies. For empirical ANN model, trained weight file of selected network architecture (20–20–1) can be taken for further validation. During validation, ANN model was proved to be better than SCS CN model. That may be because of extensive training of the network in case of ANN model which takes into account all the factors affecting rainfall-runoff relationship in the training data which was beyond the scope of SCS CN model. In addition to that, runoff from the catchment was predicted using rainfall data of only five rain-gauge stations. The performance of the catchment module was evaluated on the basis of performance criteria ME and CRM. Runoff from catchment as inflow to Kangsabati reservoir was predicted using ANN technique better match with observed inflow than distributed SCS CN method. It was concluded that IRCIM can provide reliable information on inflow to reservoir under different data availability conditions.

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