Conference Paper, Published Version

Khadr, Mosaad; Schlenkhoff, Andreas

Integration of Data-Driven Modeling and Stochastic Modeling for Multi-purpose Reservoir Simulation

ICHE 2014, Hamburg - Lehfeldt & Kopmann (eds) - © 2014 Bundesanstalt für Wasserbau ISBN 978-3-939230-32-8

Integration of Data-Driven Modeling and Stochastic Modeling for Multi-purpose Reservoir Simulation

M. Khadr
Irrigation and Hydraulics Engineering Department -Faculty of Engineering, Tanta University, Egypt
A. Schlenkhoff
Institute for Geotechnics, Waste Management & Hydro Sciences (IGAW), University of Wuppertal, Wuppertal, Germany

ABSTRACT: In reservoir management practices, a simulation model can be used as a valuable planning tool to evaluate the impact of changes to the system's configuration or operational objectives. The desired generation or release scheduling can be checked using inflow forecasting in order to satisfy the entire set of operational constraints. At real-time operation stage, a simulation tool can be used to quickly check operational alternatives due to emergency events or planning and real-time incongruence. In this paper, an integration of data-driven modelling, which is based on computational intelligence and machine-learning methods, and stochastic models for reservoir operation and simulation was presented. Adaptive network-based fuzzy inference system (ANFIS) provides a method for fuzzy modeling to learn information about the data set that best allow the associated fuzzy inference system to trace the given input/output data. The applicability and capability of the ANFIS model were investigated through the use of a set of data in the Ruhr reservoirs system, Germany. The historical data included inflow, reservoir storage, Standardized Precipitation Index (SPI) and reservoir release. Neural Networks, ANFIS, Thomas-Fiering model, and Hidden Markov Model (HMM) were integrated in a simulation model. The set of input included the time of the year, storage, inflow and Standardized Precipitation Index (SPI). The target output was the reservoir release. Predicted release values and observed release values are evaluated using several common evaluation criteria. Results of model performance showed that the ANFIS and the proposed stochastic models provided reliable reservoir release prediction. Results showed also that the proposed approach could be a good tool for the evaluation of release for a specified month and could be also a helpful reference guide to the operator during making decisions.

Keywords: Data-Driven Modeling, Stochastic Modeling, Reservoir Operation, Drought, Standardized Precipitation Index SPI

1 INTRODUCTION

Reservoir operation is a complex problem that involves many decision variables, multiple objectives as well as considerable risk and uncertainty (Husain, 2012; Mohan S 2007). Reservoir managers have to simultaneously meet requirements for different needs, such as flood control, power generation, and recreational use of the reservoir pool, environmental quality downstream of the reservoir, and the safety and structural integrity of the dam itself. In addition, the conflicting objectives lead to significant challenges for operators when making operational decisions, and engineers have created reservoir simulation models to help develop those release schedules. The desired generation or release scheduling can be checked using inflow forecasting in order to satisfy the entire set of operational constraints (Cicogna et al., 2009). At the real time operation stage, a simulation tool can be used to quickly check operational alternatives due to emergency events or planning and real-time incongruence. The operational models were broadly categorized into descriptive simulation, prescriptive optimization and hybrid simulation and/ or optimization models involving elements of both (McMahon, 2009). Descriptive simulation models are most useful for studying the operation of complex physical and hydrological characteristics of a reservoir system including the experience and evaluation of predefined operating rules. One of the main operational goals in the management of reservoirs is to determine a suitable release based on observation data and other conditions (Kamodkar, 2010). Data-driven models are becoming more common approach in in several water management issues. Data-driven modelling (DDM) is based on analyzing of the data characterizing the system under study, in particular a model can be defined on the basis of finding connections between the system state variables (input, internal and output variables) without explicit knowledge of the physical behavior(Abrahart et al., 2008). DMM is focused on computational intelligence, which includes neural networks, fuzzy systems and evolutionary computing as well as other areas within artificial intelligence and machine learning. The use of ANNs and Fuzzy logic has many successful applications in hydrology, in modelling rainfall-runoff processes: Hsu et al. (Hsu et al., 1995); Minns and Hall (Minns AW, 1996); Dawson and Wilby (Dawson CW, 1998); Dibike et al. (Dibike Y, 1999); Abrahart and See (Abrahart RJ, 2000); Govindaraju and Ramachandra Rao; replicating the behaviour of hydrodynamic/hydrological models of a river basin where ANNs are used to provide optimal control of a reservoir (Solomatine DP, 1996); for modelling stage-discharge relationships(Sudheer KP, 2003); simulation of multipurpose reservoir operation (Fontane, 1997; Shrestha et al., 1996); deriving a rule base for reservoir operation from observed data (Chuntian, 1999 ; Panigrahi and Mujumdar, 2000 ; S.Mohan and Prasad, 2006). In this paper, a simulation model for reservoir operation was developed based on the Integration of Data-Driven Modeling (ANFIS) and Stochastic Modeling (Hidden Markov model – HMM, Thomas-Fiering model). The applicability and capability of developed model were investigated through the use of a data set of the Bigge reservoir in the Ruhr basin, Germany.

2 METHODOLOGY

2.1 *Study Region and Data Collection*

The study was conducted on the Bigge reservoir which is located in the Ruhr river basin, Germany and lies in the southern part of the Sauerland between Olpe and Attendorn. The reservoir serves primarily to store and discharge water on demand, thus ensuring a balanced water level of the River Ruhr (Ruhrverband, http://www.ruhrverband.de). Up to 40 per cent of the required compensation water for all dams and reservoirs can be discharged from the Bigge Reservoir via the Bigge and Lenne rivers into the Ruhr river system. The reservoir system in the Ruhr Basin is centrally managed by the Ruhr River Association (Ruhrverband), whose major tasks are to provide drinking water and to supply local industry with process water within one of the most densely populated and industrialized areas in Europe. Maniak (Maniak, 1997) reported that 70% of the water demand of the Rhenish-Westphalian industrial zone is covered by the Ruhr and this percentage increases in dry periods. In times of extreme droughts it increases up to the 1.6 fold of the annual average. Table.1 presents some characteristical data of the Bigge reservoir. The statistical properties of the monthly inflow, monthly storage and the monthly release during the study period are listed in Table 2.

Table 1. Main data of the Bigge reservoir.(Renz, 1983)

Gross storage capacity (m^3*10^6)	171.7
Dead storage capacity (m^3*10^6)	7.5
Net storage capacity (m^3*10^6)	164.2
Amount of drinking water* (m^3*10^6)	4.0
Effective storage capacity (m^3*10^6)	160.2
Average annual inflow (m^3*10^6)	225.25
Percentage of the effective storage capacity of the system (%)	39.2
Storage ratio (storage capacity / annual inflow)	o.72
Surface area at maximum storage	8.76 km^2

Table 2. Statistical properties of the input data used in this study (1990 -2008)

Month	Inflow (million m^3)				Storage (million m^3)				Release(million m^3)			
	Mean	Min.	Max.	Std.	Mean	Min.	Max.	Std.	Mean	Min.	Max.	Std.
January	41.58	3.98	74.66	21.27	136.95	113.89	153.07	9.06	41.62	13.02	78.17	20.19
February	28.56	5.45	75.87	18.70	136.90	103.65	157.20	11.12	22.43	7.27	56.97	14.16
March	32.07	8.63	52.42	13.98	143.04	103.72	165.26	14.10	20.64	3.70	44.08	11.26
April	15.29	4.22	27.23	8.22	154.46	114.00	170.11	13.96	14.37	3.27	31.16	8.16
May	9.69	4.01	24.67	5.51	155.39	115.11	169.79	14.68	10.54	3.81	21.04	3.61
June	6.54	3.08	18.86	4.10	154.55	115.92	168.72	14.99	13.02	4.65	21.39	4.19
July	7.68	1.89	28.59	6.84	148.06	114.36	167.30	15.08	14.65	6.44	27.16	4.13
August	8.70	1.51	48.88	10.71	141.09	108.30	164.04	16.16	17.70	9.43	58.66	10.71
September	11.04	2.10	43.68	10.50	132.09	93.88	154.26	15.88	16.56	5.26	44.04	8.29
October	17.15	4.40	75.08	15.93	126.58	85.09	149.93	17.13	18.33	9.52	69.70	13.62
November	28.21	7.88	55.37	14.86	124.50	91.31	155.31	17.99	24.64	7.28	63.79	15.45
December	34.81	14.05	69.53	13.93	128.07	93.84	144.88	14.49	25.93	2.44	52.80	14.61

2.2 *Adaptive Neuro-Fuzzy Inference System - ANFIS*

Fuzzy systems present particular problems to a developer then rules have to be determined somehow (Zadeh, 1973). An adaptive neuro-fuzzy inference system (ANFIS) is a fuzzy inference system formulated as a feed-forward neural network. Hence, the advantages of a fuzzy system can be combined with a learning algorithm (Venugopal et al., 2010). Neuro-fuzzy modeling is a technique for describing the behavior of a system using fuzzy inference rules within a Neural Network (NN) structure. Using a given input/output data set, adaptive neuro-fuzzy inference system (ANFIS) constructs a FIS whose member ship function parameters are tuned using a back propagation algorithm (Labani M.M., 2010). So, the FIS could learn from the training data. In this study, the ANFIS model was developed in the MATLAB environment. ANFIS was used to extract the relation of time of year (months), storage, inflow, and Standardized Precipitation Index (SPI) and release variables and represent them as fuzzy if-then rules. The premise part of fuzzy if-then rules is months, inflow, storage, and SPI. The consequent part is the release. The structure of the ANFIS model consists of a Sugeno type fuzzy system with generalized bell input membership functions and a linear output membership function. The network consists of 8 inputs, each with 5 input membership functions, 5 rules and 1 output membership function (figure 1). The training algorithm consists of backpropagation and least squares estimation for the adjustment of premise and consequent parameters of the ANFIS respectively.

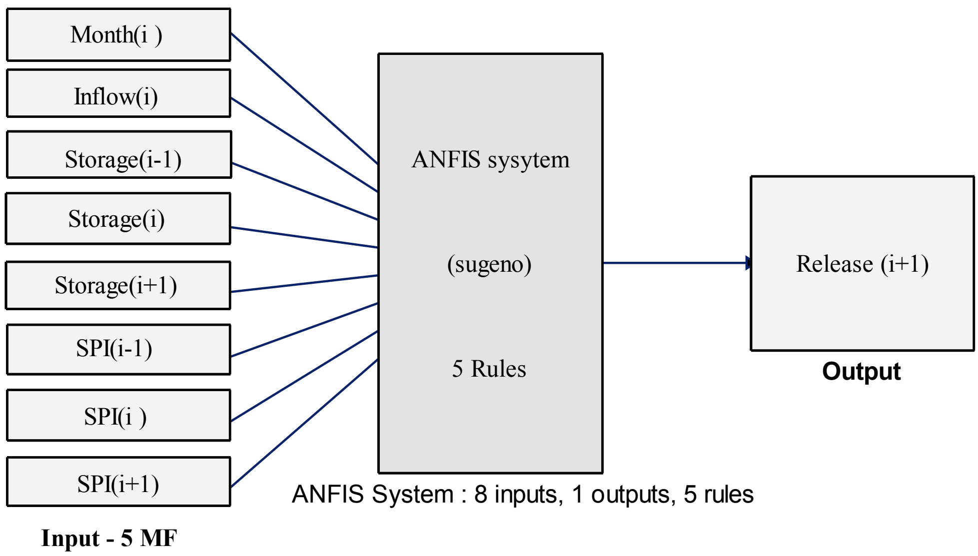

Figure 1. Architecture of the proposed Adaptive Neuro-Fuzzy Inference System

2.3 *Thomas-Fiering model for inflow generation*

The historical records of the monthly inflow were used for training and testing the developed model. To simulate the reservoir operation, monthly streamflow data were generated by using Thomas-Fiering model. Basically, this model is of a Markovian nature with periodic parameters, namely, the monthly means, standard deviations and the lag-zero cross correlations between successive months(Sen, 1978). In its simplest form the model consists of twelve regression equations, one for each month. The method of Thomas and Fiering implicitly allows for the non-stationarity observed in monthly inflow data (Singhal et al., 1980). For the Thomas-Fiering model, synthetic monthly series is generated with the following recursive relationship:

$$Q_{i+1} = \bar{Q}_{j+1} + b_j \left(Q_i - \bar{Q}_j\right) + t_i * S_{j+1} * \left(1 - r_j^{2}\right)^{1/2} \tag{1}$$

Where:

Q_i = the inflow during the *i* month record from the start of the synthetic sequence.
Q_{i+1} = the inflow during the (*i+1*) month.
$\bar{Q}_j$ = the mean monthly inflow during the j month with a repetitive cycle of 12 months.
$\bar{Q}_{j+1}$ = the mean monthly inflow during the month (*j+1*).
b_j = the regression coefficient for estimating the flow in the month *j+1* from the month *j*.
t_i = a normal random deviate with mean equal to zero and unit variance.
S_{j+1} = the standard deviation of the inflow in the month *j+1*.
r_j = the correlation coefficient between the inflows of the *j* and *j+1* month.

Initially a known streamflow of any month (say, January) along with the mean and standard deviation of historical streamflow for that month were fed to equation 1. The output produced by this equation is the streamflow of the succeeding month. The sequence of the inflow generated by equation 1 possesses the same general statistical properties as those representing natural inflow.

2.4 *HMM for SPI forecasting*

The Markov chain is a probabilistic model used to represent dependences between successive observations of a random variable (Keilson, 1979). In this study, a Hidden Markov Model (HMM) with 7 states to forecast SPI values at short-medium term has was developed. States 1 to 7 - according to SPI classification-can be interpreted as extreme events, namely extremely wet event (possible flood) and respectively meteorological severe drought (Khadr et al., 2009). The SPI was calculated for different time scales (1month, 3 months, 12 months, 48 months, etc.) based on streamflow data series which means that the drought index from the streamflow series was used as one of measures for streamflow deficit. The distinctive feature of this method is that the drought management and monitoring would be effective because of the more realistic judgment on the drought severity (Yoo et al.). The HMM was tested and results of testing periods show that Hidden Markov Model provides a good agreement between observed and forecasted values. The forecasted values of SPI (SPI (*i+1*)) were then used as input for the ANFIS model shown in figure 1.

3 RESULTS AND DISCUSSION

In this study, the developed simulation model consists of two stages. In the first stage, operation rules were developed using fuzzy approach, then the developed fuzzy inference system “FIS” was an input to the ANFIS system. In second stage, the operation of reservoirs was simulated for any required number of years using the final FIS developed by using ANFIS. Thomas-Fiering model was used to generate monthly inflow, and a HMM model was developed to forecast SPI index. In order to begin the training using ANFIS, an initial fuzzy inference system “FIS” was needed first. In the present study 42 years of historical data of inflow and 18 years of historical data of storage and release were collected. From this data, 14 years of data were used for building (training) the model and 4 years of data were used to test the model on monthly basis. As shown in table 3, the data set contains 8 input data and one output (reservoir release). FIS, fuzzy inference system, was generated using fuzzy subtractive clustering to develop a set of rules and membership functions that models the data behavior. Then the generated FIS was used as an initial FIS, initial conditions, for ANFIS training. The FIS was then evaluated to obtained output data which is the predicted value of the release. Forecasted release values and observed release values for training period and test period are shown in figure 2 and 3 respectively. In order to evaluate the performance of the ANFIS system, it is necessary to introduce evaluation criteria. In this study, the performance of the models was assessed using four statistical criteria include; Mean Absolute Deviations (MAD), R-squared, Root Mean Square Error (RMSE) and correlation coefficient (C_r) were used (table 4).

Table 3. Typical one year sample of input and output data of the simulation model

Model Input								Output
Month (i)	Inflow (i)	Storage (i-1)	Storage (i)	Storage (i+1)	SPI (i-1)	SPI (i)	SPI (i+1)	Release (i+1)
1	38.95	128.66	145.47	132.08	0.34	0.45	-0.58	10.60
2	6.64	145.47	132.08	128.12	0.45	-0.58	-1.06	6.33
3	16.99	132.08	128.12	138.78	-0.58	-1.06	-2.17	8.87
4	5.55	128.12	138.78	135.46	-1.06	-2.17	-1.56	7.88
5	5.85	138.78	135.46	133.43	-2.17	-1.56	-0.87	8.34
6	11.06	135.46	133.43	136.16	-1.56	-0.87	-0.11	11.97
7	7.26	133.43	136.16	131.45	-0.87	-0.11	-0.11	16.81
8	2.57	136.16	131.45	117.21	-0.11	-0.11	-0.78	16.16
9	2.15	131.45	117.21	103.21	-0.11	-0.78	-1.43	12.25
10	4.40	117.21	103.21	95.36	-0.78	-1.43	0.23	10.25
11	46.05	103.21	95.36	131.16	-1.43	0.23	0.67	30.51
12	43.48	95.36	131.16	144.13	0.23	0.67	0.46	25.99

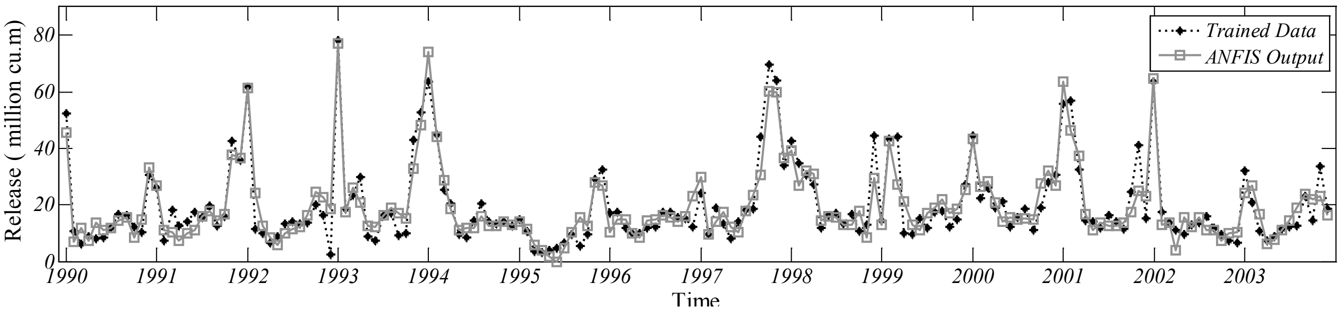

Figure 2. Comparison of historical reservoir release and ANFIS output (training period)

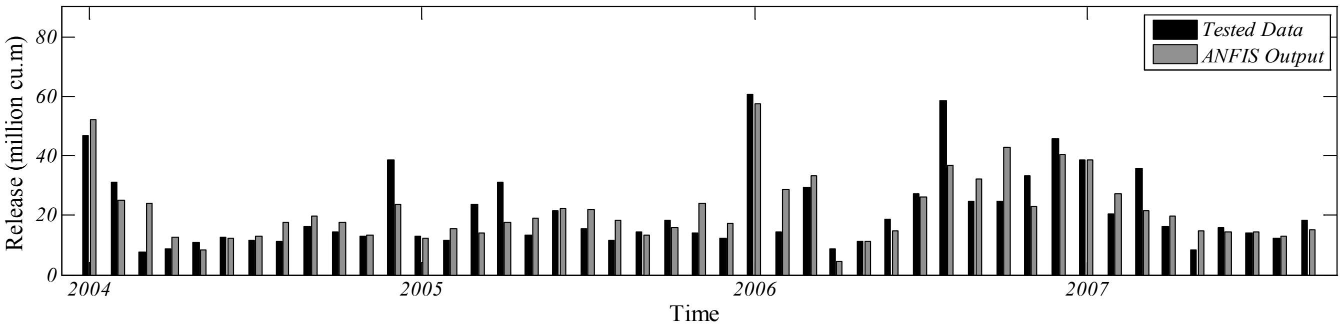

Figure 3. Comparison of historical reservoir release and ANFIS output (test period).

Table 4. Results of the simulation model performance

Studied data	Model evaluation criteria			
	RMSE	R^2	MAD	C_r
Training data	5.17	0.95	3.92	0.93
Test data	7.82	0.90	5.75	0.79

After evaluation of the ANFIS model, the FIS system could be used for simulation of reservoir operation for any required number of years as shown in figure 4. The simulation process could be illustrated as follow: In the model the set of input consists of 8 variables (table 3). At any month t, it is required to predict reservoir release at the next month *t+1*.The inflow of month *t+1* is unknown, therefore Thomas-Fiering model was used to generate monthly inflow for the month *t+1*; from historical data, storages of previous, current, and next month are known. As mentioned before, the storage volume is the storage at the beginning of any month so storage at months *t-1*, t and *t+1* are known. After holding the previous steps, three input variables were remaining unknown, namely SPI index for months *t-1*, *t*, and *t+1*. SPI for month *t-1* was calculated from historical data, and SPI for month t was calculated based on the generated inflow from Thomas-Fiering Model. SPI index for month *t+1* is predicted using the HMM.

Once the input data were available, the developed FIS system predicted the release and this process could be repeated for any number of months. The simulation model of a reservoir system is based on water balance of reservoirs. The output of the model (release) must satisfy the constraints of storage and demands. The simulation model subject several constraints such as Storage Continuity, Storage Limits, Demands limit which is identified by the reservoir operator. Figure 5 presents comparison between historical and simulated reservoir release for a period of 20 years. To simulate the behavior of the reservoir storage, a period of 500 year was simulated. Table 5 presents the driest year (based on the monthly inflow during this year) in the simulated period. Results of simulation showed that the reservoir storage reached a minimum value of 64 million m^3. The probability that the reservoir storage reached values less than 85 $M.m^3$ during the simulated period was about 0.15. It is worth to be mentioned that, in the available historical records, the minimum reservoir storage was 53.1 million m^3 in month December-1976 and the minimum release from the reservoir month was 0.535 million m^3 in month April of the year1979. Real-time reservoir operation requires a quick system response for calculation and rational decision making using available monitored data (Khattree and Rao, 2003). A quick response to an operator request is of utmost importance for a real-time decision support system. The developed ANFIS simulation model gives the best assistance for these issues by comparing the similarities of the current events and the historical data. One of the important features of the developed model its ability to forecast the release of next month based on the inflow of current month, storage of next month and considering the accuracy of SPI forecasting using HMM. By considering the value of the release confidence factor, the operator can decide on the actual release and the starting time for operation.

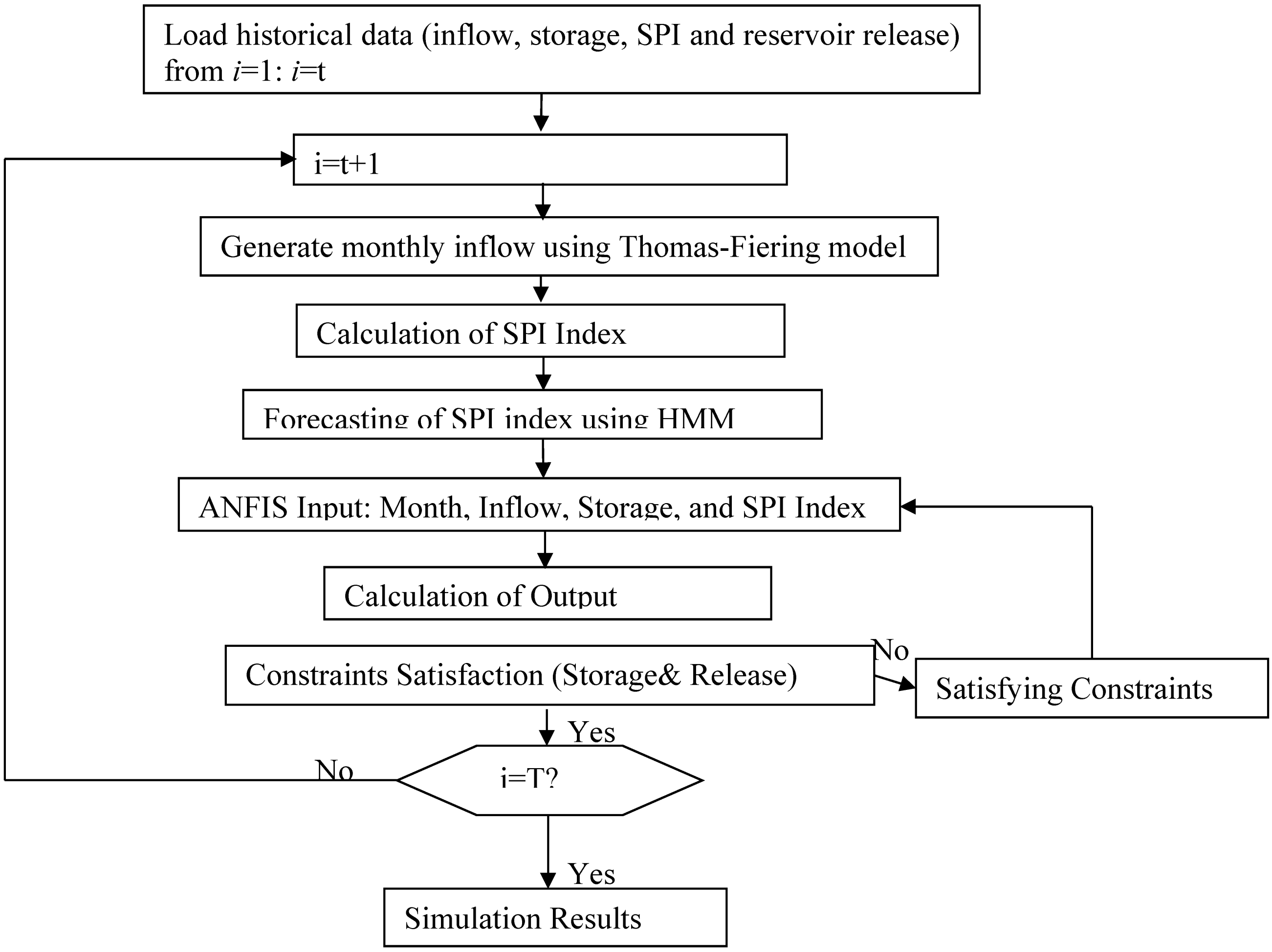

Figure 4. Flowchart of the calculation for reservoir simulation

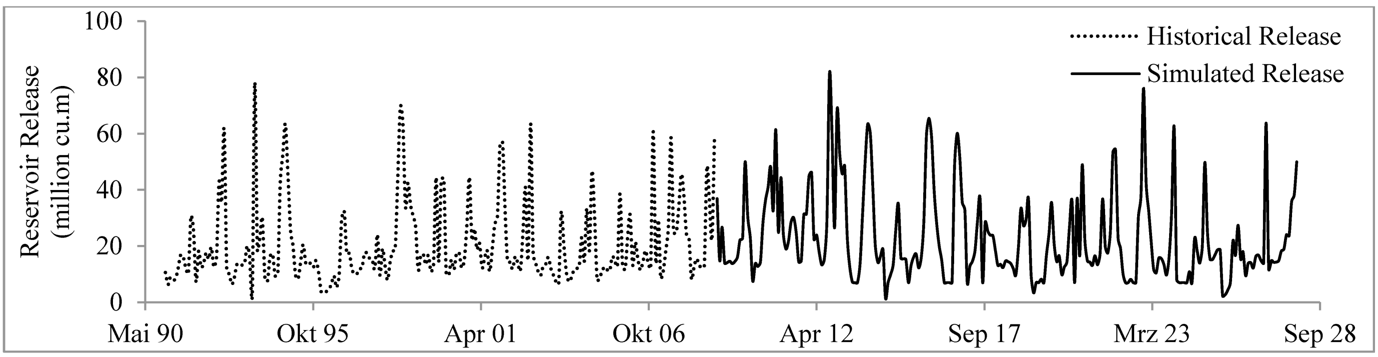

Figure 5. Results of simulated operation using the ANFIS model (20 years simulation period)

Table 5. The driest year in 500 simulated years using ANFIS, Thomas-Fiering and HMM models

Model Input								Output
Month (i)	Inflow (i)	Storage (i-1)	Storage(i)	Storage (i+1)	SPI (i-1)	SPI (i)	SPI (i+1)	Release (i+1)
1	33.03		138.00	131.71	0.24	0.16	0.00	20.17
2	8.52	138.00	131.71	120.06	0.16	-0.48	0.32	20.88
3	10.48	131.71	120.06	109.67	-0.48	-0.84	-0.56	12.47
4	5.91	120.06	109.67	103.10	-0.84	-0.99	-0.40	10.75
5	4.62	109.67	103.10	96.97	-0.99	-0.99	0.08	9.71
6	3.36	103.10	96.97	90.61	-0.99	-1.22	-1.39	11.99
7	1.89	96.97	90.61	80.52	-1.22	-1.32	-1.27	17.12
8	1.51	90.61	80.52	75.00	-1.32	-1.86 *	-1.77*	12.17
9	6.66	80.52	75.00	75.00	-1.86*	-2.51 **	-2.62**	5.00
10	4.40	75.00	75.00	74.40	-2.51**	-2.80 **	-2.10**	5.70
11	12.12	75.00	74.40	80.82	-2.80**	-2.60 **	-2.30**	7.08
12	26.51	74.40	80.82	101.43	-2.60**	-2.11 **	-2.34**	12.50

* Severely dry event ** Extremely dry event

To assess the model performance during actual drought periods, the year 1976 (which was an extremely dry period) was selected as a case study. At the first step, The ANFIS system was developed. After that, a period of 24 months, starting from January 1976, was generated to be the first input of the simulation model. Inflow records were assumed to be the same as historical inflow records during this period and the storage of the first month (January 1976) was the same as historical one. To get SPI values for the simulated periods, the SPI values were forecasted using HMM. After a simulation run, the simulated monthly release and monthly storage were then obtained. The comparisons of the observed and simulated results of the ANFIS model for the 1976 drought event are depicted in figures 6 and 7. Results showed that the reservoir release and storage were well reproduced by the simulation model during this dry period.

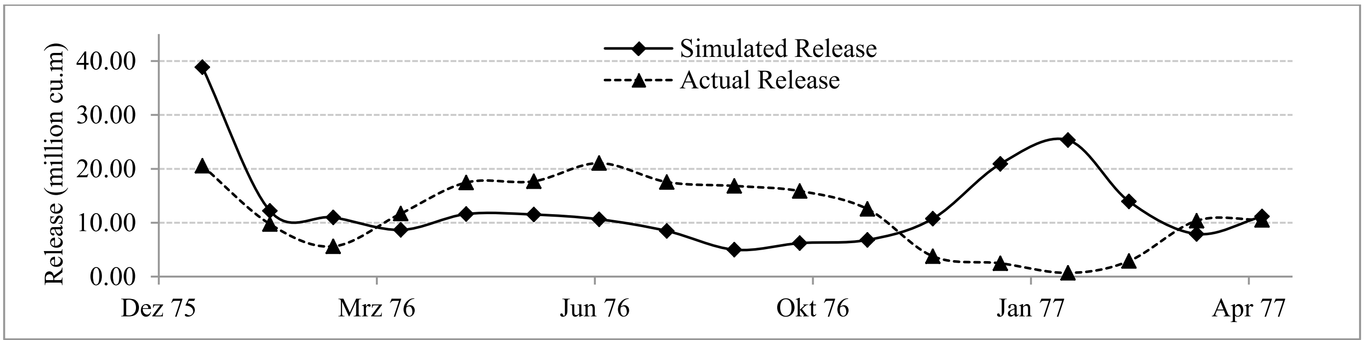

Figure 6. Comparison of the reservoir releases during the dry period 1976 and output of the simulation model

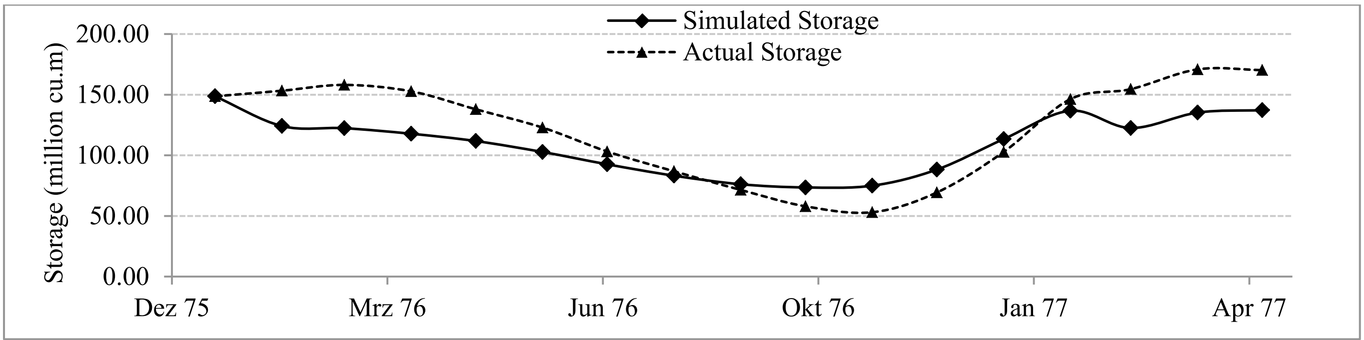

Figure 7. Comparison of the reservoir storages during the dry period 1976 and output of the simulation model

4 CONCLUSION

In this study, artificial intelligence tools and stochastic methods were used to construct a model for simulation of reservoir operation. The applicability and capability of the ANFIS model were investigated through the use of a set of data included monthly records of inflow, storage, SPI and reservoir release. The results of model performance show that integration of Neural Networks, ANFIS, Thomas-Fiering model, and HMM could provide very useful data for reservoir characterization and development.

The main conclusion of this paper is that ANFIS and Neural Networks have a great ability in determining relationships between a series of inflow, storage, and SPI data and reservoir release as target. The developed model could be used to check and evaluate different operational policies and to compare planning strategies for operation.

ACKNOWLEDGMENTS

The authors would like to express their sincere thanks to the Ruhr river association (Ruhrverband) for their assistance in providing the data for this study.

REFERENCES

Abrahart, R. et al., 2008. Data-Driven Modelling: Concepts, Approaches and Experiences, Practical Hydroinformatics. Water Science and Technology Library. Springer Berlin Heidelberg, pp. 17-30.

Abrahart RJ, S.L., 2000. Comparing neural network and autoregressive moving average techniques for the provision of continuous river flow forecast in two contrasting catchments. . Hydrological Processes 14

Chuntian, C., 1999 Fuzzy optimal model for the flood control system of the upper and middle reaches of Yangtze River. Hydrological Sciences Journal 44(4): pp. 573 - 585.

Cicogna, M.A., Fontane, D.G., Hidalgo, I.G. and Lopes, J.E., 2009. Multireservoir Simulation Using Multipurpose Constraints and Object-Oriented Software Design. In: S. Steve (Editor). ASCE, pp. 508.

Dawson CW, W.R., 1998. An artificial neural network approach to rainfall-runoff modelling. Hydrological Sciences Journal 43 (1).

Dibike Y, S.D., Abbott MB 1999 On the encapsulation of numerical-hydraulic models in artificial neural network. Journal of Hydraulic Research 37(2).

Fontane, D.G., Gates, T. K., and Moncada E., 1997. Planning reservoir operations with imprecise objectives J. Water Resour. Plan. Manage.,ASCE, 123(3) 154-162.

Hsu, K.-l., Gupta, H.V. and Sorooshian, S., 1995. Artificial Neural Network Modeling of the Rainfall-Runoff Process. Water Resources Research, 31(10): 2517-2530.

Husain, A., 2012. An Overview of Reservoir Systems Operation Techniques International Journal of Engineering Research and Development 4(10).

Kamodkar, D.R.a.R., 2010. Derivation of Multipurpose Single Reservoir Release Policies with Fuzzy Constraints. Journal of Water Resource and Protection, 2 (12): 1030-1041.

Keilson, J., 1979. Markov chain models--rarity and exponentiality. Applied mathematical sciences. Springer-Verlag, New York, xiii, 184 p. pp.

Khadr, M., Morgenschweis, G. and Schlenkhof, A., 2009. Analysis of Meteorological Drought in the Ruhr Basin by Using the Standardized Precipitation Index. International Conference on Sustainable Water Resources Management (SWRM2009),Amsterdam - Netherland.

Khattree, R. and Rao, C.R., 2003. Statistics in industry. Handbook of statistics,. Elsevier, Amsterdam Boston, xxi, 1187 p. pp.

Labani M.M., K.-I.A., Salahshoor K., 2010. Estimation of NMR log parameters from conventional well log data using a committee machine with intelligent systems: A case study from the Iranian part of the South Pars gas field, Persian Gulf Basin, J. Petrol. Sci. Eng. , 72 (175-185.).

Maniak, U.a.R., F.W., 1997 Optimal operation of the szstem of Ruhr Reservoirs. International Asscociation on Waterpollution Research, 10: 301/311.

McMahon, G.F., 2009. Models and Realities of Reservoir Operation. Journal of Water Resources Planning and Management, 135(2): pp. 57-59.

Minns AW, H.M., 1996. Artificial neural network as rainfall-runoff model. Hydrological Sciences Journal 41(3).

Mohan S , S.S., 2007. Development of multi-reservoir systems operation using dp-based neuro-fuzzy model: a case study in papsystems, india, 4th INWEPF Steering Meeting and Symposium.

Panigrahi, D.P. and Mujumdar, P.P., 2000 Reservoir Operation Modelling with Fuzzy Logic. Water Resources Management 14: pp. 89-109.

Renz, F.W., 1983. Goals and management of the Ruhr reservoir szstem since the beginnung og our century, Proceedings of Hamburg symposium, August 1983.

Ruhrverband, http://www.ruhrverband.de.

S.Mohan and Prasad, M.A., 2006. Fuzzy Logic Model for Multi Reservoir Operation, Advances in Geosciences(A 5-Volume Set) - Volume 1 Solid Earth (SE) (pp 117-126)

Sen, Z., 1978. A mathematical model of monthly flow sequences. Hydrological Sciences-Bulletin-des Sciences Hydrologiques, 23(2).

Shrestha, B.P., Duckstein, L.E. and Stokhin, Z., 1996. Fuzzy Rule-Based Modeling of Rreservoir Operation Journal of Water Resources Planning Management 122(4): pp. 262-269.

Singhal, M.K., Singhal, H.S.S. and Maheshwari, J.B., 1980. Mathematical Modelling of Inflows to the Matatila Reservoir. Hydrological Forecasting - (Proceedings of the Oxford Symposium, April 1980 IAHS-AISH Publ. no. 1 29.

Solomatine DP, T.L., 1996 Neural network approximation of a hydrodynamic model in optimizing reservoir operation, Proc. 2nd Int. Conference on Hydroinformatics, Balkema: Rotterdam.

Sudheer KP, J.S., 2003 Radial basis function neural network for modeling rating curves. ASCE Journal of Hydrologic Engineering 8(3).
Venugopal, C., Devi, S.P. and Rao, K.S., 2010. Predicting ERP User Satisfaction―an Adaptive Neuro Fuzzy Inference System (ANFIS) Approach Intelligent Information Management 2: pp. 422-430
Yoo, W.-H., Kim, H.-S. and Seoh, B.-H., Applications of Standardized Precipitation Index to Streamflows, from http://kfki.baw.de/conferences/ICHE/2000-Seoul/pdf/201/PAP_221.PDF.
Zadeh, L.A., 1973. Outline of a New Approach to Analysis of Complex Systems and Decision Processes. Ieee Transactions on Systems Man and Cybernetics, Smc3(1): pp. 28-44.