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Hybrid neural network models for hydrologic time series forecasting

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Abstract

The need for increased accuracies in time series forecasting has motivated the researchers to develop innovative models. In this paper, a new hybrid time series neural network model is proposed that is capable of exploiting the strengths of traditional time series approaches and artificial neural networks (ANNs). The proposed approach consists of an overall modelling framework, which is a combination of the conventional and ANN techniques. The steps involved in the time series analysis, e.g. de-trending and de-seasonalisation, can be carried out before gradually presenting the modified time series data to the ANN. The proposed hybrid approach for time series forecasting is tested using the monthly streamflow data at Colorado River at Lees Ferry, USA. Specifically, results from four time series models of auto-regressive (AR) type and four ANN models are presented. The results obtained in this study suggest that the approach of combining the strengths of the conventional and ANN techniques provides a robust modelling framework capable of capturing the non-linear nature of the complex time series and thus producing more accurate forecasts. Although the proposed hybrid neural network models are applied in hydrology in this study, they have tremendous scope for application in a wide range of areas for achieving increased accuracies in time series forecasting.

Keywords: Artificial neural networks; Streamflow forecasting; Time series modelling; Rainfall–runoff process; Hydrology; Hybrid models

1. Introduction

Time series forecasting has received tremendous attention of researchers in the last few decades. This is because the future values of a physical variable, which are measured in time at discrete or continuous basis, are needed in important planning, design and management activities. The time series forecasting methods have found applications in very wide areas including but not limited to finance and business, computer science, all branches of engineering, medicine, physics, chemistry and many interdisciplinary fields. Conventionally, the researchers have employed traditional methods of time series analysis, modelling, and forecasting, e.g. Box–Jenkins methods of auto-regressive (AR), auto-regressive moving average (ARMA), auto-regressive integrated moving average (ARIMA), auto-regressive moving average with exogenous inputs (ARMAX), etc. The conventional time series modelling methods have served the scientific community for a long time; however, they provide only reasonable accuracy and suffer from the assumptions of stationarity and linearity. Artificial neural networks (ANNs) were introduced as efficient tools of modelling and forecasting about two decades ago. One can find numerous ANN applications in a wide range of areas for time series forecasting. In spite of the great deal of time and effort spent by the researchers in both conventional and soft computing techniques for time series forecasting, the need of producing more and more accurate time series forecasts has forced the researchers to develop innovative methods to model time series. One can find many studies that involve developing neural network models for time series forecasting. This paper presents a study aimed at achieving accurate forecasts of a hydrologic time series using a combination of traditional time series and neural network approaches. The paper begins with a brief review of the time series forecasting using neural networks in a wide range of fields.

2. Time series forecasting using neural networks

Neural networks have been applied in many areas for time series forecasting. This section reviews some important studies reported in literatures since early 1990s. Arizmendi et al. [1] made accurate predictions of the airborne pollen concentrations using the time series data and neural networks. The predictions were found to be better than the traditional time series

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forecasting made using pollen concentrations and other meteorological parameters. Srinivasan et al. [2] employed a four-layered feed-forward neural network trained using back-propagation (BP) to make hourly predictions of electric load for a power system. Prediction accuracies with 1.07% error on weekdays and 1.80% on weekends were achieved, which was much superior to the predictions accuracies obtained from tradition time series forecasting methods. Kaastra and Boyd [3] presented an eight-step procedure to design neural network forecasting model for financial and economic time series. Ansuj et al. [4] compared ARIMA models with BPANN models for sales forecasting in Brazil and found BPANN models to be much superior. Zhang and Hu [5] employed ANNs for forecasting British pound and US dollar exchange rates. They also evaluated the impact of the number of input and hidden neurons and the size of the data on the ANN model performance. The sensitivity analyses showed that the input neurons affect the performance more than the hidden neurons and improved accuracies can be achieved with a larger sample size. Bezerianos et al. [6] employed radial basis function (RBF) neural networks for the assessment and prediction of the heart rate variability. Li et al. [7] modelled damping in tall buildings using BPANNs and AR models. The models were used to predict the damping values at high values of vibrations, which are difficult to obtain through field measurements. Nguyen and Chan [8] proposed a multiple neural network (MNN) approach for making multistep ahead forecasts of hourly customer demand for gas at a compression station in Sask., Canada. It was found that the MNN model performed better than the single ANN model developed on the same data set.

Most of the studies reported above were simple applications of using traditional time series approaches and ANNs. Many of the real-life time series are extremely complex to be modelled using simple approaches especially when high accuracy is required. Hansen and Nelson [9] used synergic combination of neural networks and traditional time series methods to make economic forecasts using revenue data from UT, USA. They concluded that the economic forecasts resulting from synergic combination were more accurate than the individual forecasts from traditional time series and neural networks. Kalaitzakis et al. [10] investigated several approaches including Gaussian encoding BP, window random activation, RBF networks, real-time recurrent neural networks (RNNs) and their innovative variations for short-term electric load forecasting. The models proposed were able to achieve significantly more accurate forecasts as compared to the simple AR and BPANN models. In addition, they also proposed a parallel processing approach for making 24-h ahead electric load forecasts. Zhang [11] proposed a hybrid ARIMA and ANN model to take advantage of the two techniques and applied the proposed hybrid model to some real data sets. He concluded that the combined model can be an effective way to improving forecasts achieved by either of the models used separately. Gao and Er [12] made non-linear auto-regressive moving average with exogenous inputs (NARMAX) model based time series prediction with fuzzy neural networks (FNNs) using both feed-forward and recurrent methods. They also proposed an efficient algorithm for model structure determination and parameter estimation for producing improved forecasts for NARMAX time series models.

It is clear that neural networks have been applied to a wide range of disciplines for time series forecasting using simple approaches. Some recent studies clearly demonstrate that there is a strong need to exploit the advantages of both traditional time series methods and ANNs in order to achieve increased accuracy in time series forecasting. Although one can find many applications of developing hybrid models in a variety of areas, such attempts have been limited in hydrology and water resources system modelling. The next section is devoted to explaining the problem of hydrologic modelling, its need and the state of art in hydrologic time series modelling.

3. Hydrologic time series modelling

One of the key hydrologic variables is the streamflow at a location in a river in a catchment, which is measured in cubic metres per second. The availability of accurate streamflow forecasts at a location in a river in a catchment is important in many water resources management and design activities such as flood control and management and design of various hydraulic structures such as dams and bridges. Streamflow forecasts can be generated using two types of mathematical models: rainfall–runoff models that use both climatic and hydrologic data and streamflow models that use only the hydrologic data. Usually, the researchers have relied on conventional modelling techniques, either deterministic/conceptual models that consider the physics of the underlying process or systems theoretic/black-box models that do not. Deterministic and black-box models of varying degree of complexity have been employed in the past for modelling rainfall–runoff process with varying degree of success. The streamflow process in a catchment is a complex and non-linear process affected by many and often interrelated physical factors. The factors affecting the streamflow response of a catchment subjected to rainfall input include: (a) storm characteristics, i.e. intensity and duration of rainfall events, (b) catchment characteristics, i.e. size, shape, slope and storage characteristics of the catchment, percentage of the catchment contributing streamflow at the outlet at various time steps during a rainfall event, (c) geomorphologic characteristics of a catchment, i.e. topography, land use patterns, vegetation and soil types that affect the infiltration and (d) climatic characteristics such as temperature, humidity and wind characteristics. The influence of these factors and many of their combinations in generating streamflow is an extremely complex physical process and is not understood clearly [13]. Moreover, many of the deterministic or conceptual rainfall–runoff models need a large amount of data for calibration and validation purposes and are computationally extensive. As a result, the use of deterministic/conceptual models of the rainfall–runoff process has been viewed rather sceptically by the researchers and has not become very popular [14]. ANNs have been proposed as efficient tools for modelling and prediction and are supposed to possess the capability to reproduce the unknown relationship existing between a set of input explanatory variables and output variables [15]. Many studies have demonstrated that the ANNs are adequate to model the runoff process and can even perform better than the conventional modelling techniques [13,16–22].

A lot of effort has been spent in using the traditional time series analysis techniques for streamflow forecasting. Many models of varying degree of complexity and sophistication have been proposed by various researchers. Some of the earliest examples of the AR type of streamflow forecast models include Thomas and Fiering [23] and Yevjevich [24]. Since then, several researchers have engaged in extensive research toward improving early concepts and developing various models of hydrologic time series. Yevjevich [25] developed AR models using 69 years of monthly streamflow data for Lake Michigan-Huron. Carlson et al. [26] proposed significant developments in the form of ARMA models of the hydrologic time series. McKerchar and Delleur [27] used the ARIMA modelling to model monthly streamflow of 16 watersheds in Indiana, Illinois and Kentucky. An important contribution to the time series modelling was due to Kalman [28], in the form of model capability to operate in an adaptive sense. He provided a mechanism, which could minimize the forecast error variance. This mechanism, called Kalman filter, provides a well defined algorithm for automatically updating parameter estimates of a model, in order to forecast recursively using the latest information. Some other notable examples of the use of time series modelling for streamflow forecasting include Bolzern et al. [29], Lettenmaier [30], Burn and McBean [31], Bender and Simonivic [32] and Awwad et al. [33]. The ANN modelling of streamflow using only flow data and the comparison of ANN models with the time series models have been limited in hydrology. Atiya et al. [34] compared time series and ANN models for making single-step and multiple-step ahead forecasts for river flow. Jain et al. [35] compared the ANN models with regression and time series models in making short-term water demand predictions at the Indian Institute of Technology, Kanpur. Jain and Ormsbee [36] used ANN to model the short-term water demand process in KY, USA, and found its performance to be better than the regression and time series models of AR type. Jain and Indurthy [37] used past flow information to model the complex rainfall–runoff process and compared the same with the regression models. Coulibaly et al. [38] presented multilayer perceptron (MLP), input delayed neural network (IDNN) and recurrent neural network with and without input delays for reservoir inflow prediction in the Chute-du-Diable catchment in Canada. Apart from these studies, the efforts in the area of using ANNs for time series modelling and prediction in hydrology have been limited.

While developing ANN models of the hydrologic time series, most of the researchers have employed raw data to be presented to the ANN. The raw data consist of various trends in the form of long-term memory and seasonal variations. For these reasons, the hydrologic time series may be non-stationary affecting the performance of the ANN models. It may be possible to improve the performance of ANN models by first carefully removing the long-term and seasonal variations before presenting an ANN with the modified data. The conventional time series modelling approaches of ARMA type suffer from being based on the linear systems theory. The non-linear and massively parallel structure of ANNs coupled with traditional time series methods may provide robust modelling framework capable of producing more accurate forecasts; however, it needs to be investigated. The objectives of the study presented in this paper are to: (a) investigate the use of non-linear ANNs for modelling the complex hydrologic time series, (b) evaluate the impact of first removing the long-term and seasonal variations in a time series before presenting the filtered data to an ANN on prediction and modelling in an attempt to develop hybrid models and (c) compare the performance of the proposed approach with the traditional time series models. In all, four time series models of AR type and four ANN models are presented. All the models and the proposed methodologies are tested using the monthly streamflow data derived from the Colorado River at Lees Ferry, USA. The development of various models is presented next.

4. Model development

Two types of approaches have been investigated in this study for the purpose of streamflow forecasting. The first approach involves the conventional time series modelling of AR type and the second one uses ANN approach. In addition, each of the two approaches is tested on three categories of data: raw data consisting of monthly flows (m^3/s), de-trended data consisting of modified data after removing long-term trends and the de-trended de-seasonalised data after removing long-term trends and seasonal variations. The purpose of using the two additional data categories was to evaluate the impact of de-trending and de-seasonalisation steps of time series modelling on the performance of ANN models. The ANN models developed on data in second and third categories represent hybrid models. Monthly streamflow data for a period of 62 years (1911–1972) derived from the Colorado River at Lees Ferry, CO, USA, were employed for the model development in this study. Colorado River is one of the major rivers in USA and experiences floods every year. There are many dams constructed across the Colorado River at various locations for flood control and other purposes. The reservoir operation at these dams requires monthly streamflow forecast models. The streamflow data for the first 40 years (1911–1950) were employed for calibration/training and the data for the remaining 22 years were employed for testing purposes.

4.1. Auto-regressive models

The steps involved in developing a time series model of AR type include modelling of long-term trends, modelling of seasonal variations and modelling of the auto-correlation structure of the time series. The long-term trends were removed by subtracting the annual average streamflow from the original time series to obtain the de-trended time series. The seasonal variations can be modelled using either the arithmetic mean or the Fourier mean approach. The latter approach was employed in this study for its smoothness and superiority in modelling the seasonal effects and to determine the de-trended de-seasonalised time series. The data were normalized to have a mean of 0.0 and a variance of 1.0 before exploring for the auto-correlation structure. A simple normalization expression was employed for this purpose:

$$\mathrm{XN}(t) = \frac{X(t) - \bar{x}}{\sigma} \quad (1)$$

where $\mathrm{XN}(t)$ is the normalized time series variable, $X(t)$ the original time series variable, $\bar{x}$ the mean of the original time series data and σ is the standard deviation of the original time series data.

The auto-correlation and partial auto-correlation analyses suggested an auto-regressive process of order 4. However, four different AR models, namely AR(1), AR(2), AR(3) and AR(4), were developed in this study. The structure of the AR models can be represented by the following equation:

$$Q(t) = \sum_{i=1}^{p} \alpha(i) Q(t-i) + \varepsilon(t) \quad (2)$$

where $Q(t)$ is the monthly streamflow being modelled, $Q(t-i)$ the past streamflow, α's the auto-regressive parameters to be determined, p the order of the AR process, i an index representing the order of the AR process, $\varepsilon(t)$ a random variable and t is an index representing time (months in this case). In developing the AR models for the data category 1, the auto-correlation step was carried out on the raw data; for AR models in the data category 2, the auto-correlation model was developed using de-trended data; for the AR models in the data category 3, the auto-correlation models were developed using the de-trended and de-seasonalised data. This was done in an attempt to compare the performance of the AR models with the corresponding ANN models. The AR parameters can be obtained by the solution of the Yule Walker equations [39]. Once the estimates of the AR coefficients have been obtained using the calibration data set, the model can be validated by computing the performance statistics during both calibration and testing data sets.

4.2. ANN models

The feed-forward multilayer perceptron type ANN model architecture was considered in this study to develop time series models of the non-linear type in an attempt to improve the performance of streamflow forecasting. The ANN models developed in this study consisted of three layers: an input layer consisting of input explanatory variables, one hidden layer and an output layer consisting of a single neuron representing the flow to be modelled at time t, $Q(t)$. Four different ANN models were developed for each category of the data set. The first ANN model (called ANN1 model in this paper) consisted of the past streamflow $Q(t-1)$ as the input, the second ANN model (referred to as the ANN2 model) consisted of the past 2 months' streamflows, $Q(t-1)$ and $Q(t-2)$, as the inputs, the third ANN model (called ANN3 model) was formed by the input vector consisting of the last 3 months' streamflows, $Q(t-1)$, $Q(t-2)$ and $Q(t-3)$, and finally, the fourth ANN model (called ANN4 model) consisted of the past 4 months' streamflows, $Q(t-1)$, $Q(t-2)$, $Q(t-3)$ and $Q(t-4)$, at the input layer. The number of hidden layer neurons was determined using the trial and error procedure for each model under each of the data category described earlier. The data were scaled in the range of 0 and 1. The unipolar sigmoid activation function and the generalized delta rule [40] were employed in all the ANN models developed in this study. The optimum number of hidden neurons of 7, 8, 9 and 9 for category 1; 7, 9, 9 and 13 for category 2; 7, 9, 9 and 12 for category 3 were found to be the best for modelling the monthly streamflow in Colorado River at Lees Ferry for the ANN1, ANN2, ANN3 and ANN4 models, respectively. Once the best ANN architectures for each data category were obtained, they were used to compute the performance statistics during both training and testing.

5. Performance evaluation

Three different types of standard statistical performance evaluation criteria were employed to evaluate the performance of various models developed in this study. These are average absolute relative error (AARE), threshold statistics for an absolute relative error (ARE) level of $x\%$ (TS_x) and the correlation coefficient (R). The three performance evaluation criteria used in the current study can be calculated using the following equations:

$$\mathrm{AARE} = \frac{1}{N} \sum_{i=1}^{N} \left| \frac{\mathrm{QO}(t) - \mathrm{QE}(t)}{\mathrm{QO}(t)} \right| \times 100\% \quad (3)$$

$$\mathrm{TS}_x = \frac{n_x}{N} \times 100\% \quad (4)$$

$$R = \frac{\sum_{t=1}^{N} (\mathrm{QO}(t) - \overline{\mathrm{QO}})(\mathrm{QE}(t) - \overline{\mathrm{QE}})}{\sqrt{\sum_{t=1}^{N} (\mathrm{QO}(t) - \overline{\mathrm{QO}})^2 (\mathrm{QE}(t) - (\overline{\mathrm{QE}}))^2}} \quad (5)$$

where, n_x is the number of data points for which the ARE is less than $x\%$, N the total number of data points computed, $\overline{\mathrm{QO}}$ the mean of observed streamflow series, $\overline{\mathrm{QE}}$ the mean of predicted/estimated streamflow series and other variables have the same meaning as explained earlier. Threshold statistics were computed for ARE levels of 1, 5, 10, 25, 50, 75 and 100% in this study. Clearly, lower AARE values and higher TS_x values would indicate good model performance. Correlation coefficient values close to 1.0 indicate good model performance.

The TS and AARE statistics measure the "effectiveness" of a model in terms of its ability to accurately predict data from a calibrated model and have been used in literature [22,41–43]. The other statistics, such as correlation coefficient R, quantify the efficiency of a model in capturing the complex, dynamic and non-linear nature of the physical process being modelled.

The global error statistics (e.g. R, RMSE, etc.) tend to give higher weightage to the high magnitude streamflows due to the involvement of square of the difference between observed and predicted streamflows or equivalent expressions. Therefore, the errors in estimating low magnitude streamflows are dominated by the errors in estimating high magnitude streamflows in such global statistics. The error statistics based on percentage error in prediction with respect to observed value (such as TS and AARE) are better for performance evaluations as they give appropriate weightage to all magnitude streamflows (low, medium or high). This aspect of relative errors such as AARE and threshold statistics has been found to give more appropriate assessment and comparison of various models by some researchers [22,41].

6. Results and discussions

The results in terms of various performance evaluation measures are presented in Tables 1–3 for the three categories of data, respectively, for both training/calibration and testing data sets. It can be noted from Table 1 that the performance of the four AR models in terms of all the statistics is poor during both calibration and testing and is not acceptable. On the other hand, the performance of the ANN models (ANN1–ANN4), although significantly better than the corresponding AR models, can only be categorized as reasonable. This is highlighted by the best R values of 0.68 and 0.59 only during training and testing, respectively, from the ANN4 model. The performance of AR(4) model was the best among AR models and the performance of the ANN4 model was the best among all the models for category 1,

Table 1
Performance evaluation statistics from various models for data category 1

Model	TS1	TS5	TS10	TS25	TS50	TS75	TS100	AARE	R value
During training/calibration									
AR(1)	0.00	1.02	2.32	12.52	25.62	49.52	58.65	94.67	0.48
AR(2)	0.00	1.60	3.82	14.26	27.52	50.12	60.12	92.78	0.48
AR(3)	1.89	2.89	4.89	15.52	30.58	52.72	61.63	90.42	0.50
AR(4)	1.99	3.12	6.15	16.26	32.87	53.72	62.76	88.52	0.51
ANN1	1.12	2.87	4.72	15.82	30.72	55.76	65.56	41.31	0.61
ANN2	1.87	3.01	5.72	16.90	32.81	57.82	66.87	44.51	0.62
ANN3	1.92	3.01	5.92	17.03	33.82	58.85	67.98	41.72	0.66
ANN4	1.98	3.18	6.37	18.92	34.09	58.97	68.29	44.01	0.68
During testing									
AR(1)	0.00	0.00	0.00	2.57	15.82	29.58	47.42	112.34	0.30
AR(2)	0.00	0.00	0.00	4.26	17.57	30.14	50.25	110.42	0.31
AR(3)	0.00	0.00	1.89	5.55	20.72	32.90	55.85	104.72	0.38
AR(4)	0.00	0.00	2.15	6.26	22.19	36.10	55.91	100.76	0.40
ANN1	0.00	1.92	3.72	8.61	28.72	45.09	61.97	61.98	0.51
ANN2	0.00	2.07	4.92	10.02	28.12	47.99	62.01	65.52	0.52
ANN3	0.00	2.70	5.23	12.19	33.01	47.86	61.98	60.42	0.55
ANN4	0.00	3.18	6.37	12.90	34.09	48.99	63.22	55.52	0.59

Table 2
Performance evaluation statistics from various models for data category 2

Model	TS1	TS5	TS10	TS25	TS50	TS75	TS100	AARE	R value
During training/calibration									
AR(1)	0.00	1.62	2.39	12.15	25.62	50.21	65.71	72.76	0.51
AR(2)	0.00	1.70	4.71	14.26	27.52	52.09	65.83	71.67	0.52
AR(3)	1.98	2.89	5.01	16.91	32.54	54.76	66.83	70.79	0.57
AR(4)	1.99	3.12	6.98	17.92	33.90	55.65	67.63	68.62	0.59
ANN1	2.20	4.92	7.01	15.82	30.72	58.46	75.01	18.97	0.78
ANN2	2.87	5.01	8.01	18.92	32.81	60.82	76.92	19.55	0.77
ANN3	2.92	5.61	8.92	19.06	33.82	61.83	76.98	19.11	0.77
ANN4	3.08	6.18	9.37	18.92	34.09	62.92	78.29	17.68	0.80
During testing									
AR(1)	0.00	1.92	2.38	12.52	27.62	44.52	56.02	89.92	0.42
AR(2)	0.00	1.96	3.82	13.26	28.52	45.12	56.34	89.13	0.45
AR(3)	1.91	2.89	4.89	16.52	29.52	47.75	56.72	88.52	0.48
AR(4)	2.09	3.12	6.15	16.26	32.81	48.72	56.91	87.52	0.50
ANN1	2.62	2.87	8.72	17.12	30.72	55.72	65.72	41.86	0.61
ANN2	2.87	3.01	9.72	18.26	32.81	57.82	66.62	42.01	0.66
ANN3	2.92	3.35	10.92	17.03	33.82	58.83	67.98	41.18	0.67
ANN4	3.08	4.18	10.37	18.92	34.09	58.92	68.29	39.62	0.69

Table 3
Performance evaluation statistics from various models for data category 3

Model	TS1	TS5	TS10	TS25	TS50	TS75	TS100	AARE	*R* value
During training/calibration									
AR(1)	4.44	13.14	20.55	49.52	76.11	89.52	95.62	36.74	0.72
AR(2)	4.44	12.22	20.18	48.26	75.52	89.12	95.94	36.58	0.73
AR(3)	15.18	20.74	30.01	55.52	79.81	91.72	95.62	36.32	0.79
AR(4)	15.18	22.22	29.07	54.26	79.81	92.72	96.71	35.89	0.81
ANN1	17.70	30.87	62.72	94.82	97.10	97.72	97.82	10.97	0.88
ANN2	12.87	31.01	55.72	89.92	95.81	97.82	97.88	12.55	0.86
ANN3	13.92	30.01	58.92	87.03	96.82	97.83	98.18	12.61	0.87
ANN4	12.89	31.18	60.37	88.92	96.02	97.92	98.29	9.62	0.89
During testing									
AR(1)	17.25	28.02	39.00	42.52	49.35	51.18	58.62	59.16	0.60
AR(2)	10.72	15.32	21.87	34.26	45.68	50.12	60.14	57.98	0.62
AR(3)	14.51	24.51	25.00	35.52	47.58	52.72	61.62	58.52	0.66
AR(4)	10.98	21.96	25.21	36.26	42.87	53.72	62.71	57.16	0.67
ANN1	8.24	16.42	25.39	52.82	61.72	80.72	83.42	33.26	0.73
ANN2	8.12	25.62	32.78	59.92	64.81	79.01	86.82	35.72	0.75
ANN3	7.25	28.97	40.73	55.03	63.83	78.81	89.18	35.82	0.77
ANN4	7.98	30.72	41.26	58.92	64.09	80.92	88.29	32.72	0.78

i.e. for which the original data were used for model development. Also, ANN models consistently outperformed the AR models.

Analysing the results from Table 2 when the de-trended data are employed for model development purposes, it can be observed that the trend of model performance is similar. That is, the performance of the model increases with an increase in the inputs in the form of past streamflows. The performance of the AR models improved a lot when carrying out the de-trending step as expected. The ANN4 model obtained the best AARE values of 17.68 and 39.62% and the *R* values of 0.80 and 0.69 during training and testing, respectively, highlighting its superiority over the AR models and the other ANN models. In general, all the ANN models consistently outperformed their AR counterparts for the models in category 2, when the models were developed using the de-trended data.

Analysing the results from Table 3 when the de-trended de-seasonalised data are employed for model development, it can be observed that the trends in the model performances are similar, i.e. the performance improves with an increase in the order of the AR process. The performance of the AR models improved a lot when carrying out the de-trending and de-seasonalisation steps, as expected, however, the ANN models still consistently outperformed the AR models. The AR(4) model performed the best among the AR models and obtained the best values of AARE and *R* of 35.89% and 0.81 during calibration and 57.16% and 0.67 during testing. The ANN4 model obtained the best values of AARE and *R* of 9.62% and 0.89 during training and 32.72% and 0.78 during testing. For being employed in important water resources management applications for use in monthly streamflow forecasting, it is desirable to have a model that is robust (measured by *R* value) and is able to forecast accurately (measured by TS and AARE). In order to select the best model based on the performance statistics considered in this study, a voting analysis was carried out. A vote of one was assigned to a model when it performed the best in terms of a single performance statistic. The results of the voting analysis are presented in Table 4. It is clear that the ANN model with four past streamflows as inputs and which uses de-trended and de-seasonalised data at its input layer (ANN4 model) is deemed to be the best model as it secured a maximum of 42 votes out of a possible of 53 votes (79.25%). The distant second best model was ANN1 model with five votes (9.43%). The AR models performed very poorly during the voting analysis and are therefore not suitable to model the complex time series such as the monthly streamflows.

These results demonstrate that the ANNs are better models than the time series models of AR type for the modelling of the hydrologic time series. The better performance of the ANN models indicates that the ANN models are able to capture the non-linear behaviour of the streamflow process in a river while the conventional time series models of the AR type are incapable of doing so due to their linear nature. Further, analyzing the results from the three tables, it can be noted that the performance of the models improves in terms of all the statistics as the steps involved in the time series analysis (e.g. de-trending and de-seasonalisation) are carried out before presenting the data to the ANN model. This is particularly important finding especially

Table 4
Results of the voting analysis

Serial number	Model	Votes	Percentage
1	AR(1)	0	0.00
2	AR(2)	0	0.00
3	AR(3)	1	1.89
4	AR(4)	1	1.89
5	ANN1	5	9.43
6	ANN2	2	3.77
7	ANN3	2	3.77
8	ANN4	42	79.25
Total		53	100.0

with reference to the ANN models in which the ANN models are normally developed by simply presenting the raw data to the ANN. This study is able to demonstrate that the hybrid models that combine the strengths of traditional time series methods and ANNs provide much superior forecast accuracies in the time series modelling of complex physical systems.

7. Summary and conclusions

This study presents the findings of an investigation of the use of combining ANNs and traditional time series approaches for achieving improved accuracies in time series forecasting. A new approach of modelling complex time series, capable of exploiting the advantages of both the conventional and the ANNs, is proposed. The proposed modelling framework gradually receives the data filtered using conventional methods and then uses the force-fitting behaviour of the ANNs to capture the non-linearity in the time series involved. In all, four AR type and four ANN models are presented in this paper. The monthly streamflow data from the Colorado River at Lees Ferry, CO, USA, were employed to develop all models and test the proposed methodology.

The results obtained in this study indicate that the ANNs are powerful tools to model the complex time series and need to be exploited further to take advantage. The ANNs were able to capture the hidden relationships among the historical streamflows and the future flows in a much better manner than the conventional time series models of AR type. The ANN models were able to produce more accurate forecasts as exhibited in the TS and AARE statistics. The reasons of the better performance of the ANNs over the traditional models is that they do not presuppose any functional form of the model to be developed and that they do not depend on the assumptions of linearity. Traditionally, researchers have used raw data with ANN time series modelling. The findings of this study have revealed that using mathematical filters to filter out the long-term and seasonal variations in the data first before presenting them to the ANN can be extremely useful in producing more accurate time series forecasts. However, these findings raise the question: do the ANNs also need the time series to be stationary like in the conventional time series modelling? It appears that the answer is in affirmative; however, more studies are needed to strengthen the findings reported here. It is hoped that the future research efforts will focus in some of these directions to develop better models of the complex time series.

References

[1] C.M. Arizmendi, J.R. Sanchez, N.E. Ramos, G.I. Ramos, Time series prediction with neural nets application to airborne pollen forecasting, Int. J. Biometeorol. 37 (3) (1993) 139–144.

[2] D. Srinivasan, A.C. Liew, C.S. Chang, A neural network short-term load forecaster, Electr. Power Syst. Res. 28 (3) (1994) 227–234.

[3] I. Kaastra, M. Boyd, Designing a neural network for forecasting financial and economic time series, Neurocomputing 10 (3) (1996) 215–236.

[4] A.P. Ansuj, M.E. Camargo, R. Radharamanan, D.G. Petry, Sales forecasting using time series and neural networks, Comput. Ind. Eng. 31 (1–2) (1996) 421–424.

[5] G. Zhang, M.Y. Hu, Neural network forecasting of the British pound US dollar exchange rate, Omega-Int. J. Manage. Sci. 26 (4) (1998) 495–506.

[6] A. Bezerianos, S. Papadimitriou, D. Alexopoulos, Radial basis function neural networks for the characterization of heart rate variability dynamics, Artif. Intell. Med. 15 (3) (1999) 215–234.

[7] Q.S. Li, D.K. Liu, J.Q. Fang, A.P. Jeary, C.K. Wong, Damping in buildings: its neural network model and AR model, Eng. Struct. 22 (9) (2000) 1216–1223.

[8] H.H. Nguyen, C.W. Chan, Multiple neural networks for a long term time series forecast, Neural Comput. Appl. 13 (1) (2004) 90–98.

[9] J.V. Hansen, R.D. Nelson, Neural networks and traditional time series methods: a synergistic combination in state economic forecasts, IEEE Trans. Neural Networks 8 (4) (1997) 863–873.

[10] K. Kalaitzakis, G.S. Stavrakakis, E.M. Anagnostakis, Short-term load forecasting based on artificial neural networks parallel implementation, Electr. Power Syst. Res. 63 (3) (2002) 185–196.

[11] G.P. Zhang, Time series forecasting using hybrid ARIMA and neural network models, Neurocomputing 50 (2003) 159–175.

[12] Y. Gao, M.J. Er, NARMAX time series model prediction: feed-forward and recurrent fuzzy neural network approaches, Fuzzy Sets Syst. 150 (2) (2005) 331–350.

[13] B. Zhang, S. Govindaraju, Prediction of watershed runoff using bayesian concepts and modular neural networks, Water Resour. Res. 36 (3) (2000) 753–762.

[14] R.B. Grayson, I.D. Moore, T.A. McMahon, Physically based hydrologic modelling. 2. Is the concept realistic, Water Resour. Res. 28 (10) (1992) 2659–2666.

[15] K. Chakraborty, K. Mehrotra, C.K. Mohan, S. Ranka, Forecasting the behaviour of the multivariate time series using neural networks, Neural Networks 5 (1992) 961–970.

[16] M.L. Zhu, M. Fujita, N. Hashimoto, Application of neural networks to runoff prediction, in: K.W. Hippel, et al. (Eds.), Stochastic and Statistical Methods in Hydrology and Environmental Engineering, Kluwer Academic, Norwell, MA, 1994, pp. 205–216.

[17] J. Smith, R.N. Eli, Neural network models of the rainfall runoff process, J. Water Resour. Plan. Manage. ASCE 121 (1995) 499–508.

[18] A.W. Minns, M.J. Hall, Artificial neural networks as rainfall runoff models, Hydrol. Sci. J. 41 (3) (1996) 399–417.

[19] A.Y. Shamseldin, Application of neural network technique to rainfall–runoff modelling, J. Hydrol. 199 (1997) 272–294.

[20] D.W. Dawson, R. Wilby, An artificial neural network approach to rainfall–runoff modelling, Hydrol. Sci. J. 43 (1) (1998) 47–65.

[21] M. Campolo, A. Soldati, P. Andreussi, Forecasting river flow rate during low-flow periods using neural networks, Water Resour. Res. 35 (11) (1999) 3547–3552.

[22] A. Jain, S. Srinivasulu, Development of effective and efficient rainfall–runoff models using integration of deterministic, real-coded genetic algorithms, and artificial neural network techniques, Water Resour. Res. 40 (4) (2004) W0430210.1029/2003WR002355.

[23] H.A. Thomas, M.B. Fiering, Mathematical synthesis of streamflow sequences for the analysis of river basin by simulation, in: A. Mass, et al. (Eds.), Design of Water Resources Systems, Harvard University Press, Cambridge, MA, 1962, pp. 459–493.

[24] V. Yevjevich, Fluctuations of Wet and Dry Years. Part-I. Research Data Assembly and Mathematical Models, Hydrology Paper 1, Colorado State University, Fort Collins, CO, 1963.

[25] V. Yevjevich, Generation of Hydrologic Samples: Case Study of the Great Lakes, Hydrology Paper 72, Colorado State University, Fort Collins, CO, 1975.

[26] R.F. Carlson, A.J.A. MacCormick, D.G. Watts, Application of linear models to four annual streamflow series, Water Resour. Res. 6 (4) (1970) 1070–1078.

[27] A.I. McKerchar, J.W. Delleur, Application of seasonal parametric stochastic models for monthly flow data, Water Resour. Res. (1974) 246–255.

[28] R.E. Kalman, A new approach to linear filtering and prediction problems, ASME Trans. Basic Eng. 82 (2) (1960) 35–45.

[29] P.M. Bolzern, G. Ferrario, G. Fronza, Adaptive real-time forecast of river flow rates from rainfall data, J. Hydrol. 47 (1980) 251–267.

[30] D.P. Lettenmaier, Synthetic streamflow forecast generation, J. Hydraul. Eng. ASCE 110 (3) (1984) 277–289.
[31] D.H. Burn, E.A. McBean, River flow forecasting model for Sturgeon River, J. Hydraul. Eng. ASCE 111 (2) (1985) 316–333.
[32] M. Bender, S. Simonivic, Time series modeling for long-range streamflow forecasting, J. Water Resour. Plan. Manage. ASCE 118 (6) (1992) 857–869.
[33] H. Awwad, J. Valdes, P. Restrepo, Streamflow forecasting for Han River basin Korea, J. Water Resour. Plan. Manage. ASCE 120 (5) (1994) 651–673.
[34] A.F. Atiya, S.M. El-Shoura, S.I. Shaheen, M.S. El-Sherif, A comparison between neural network forecasting techniques-case study: river flow forecasting, IEEE Trans. Neural Networks 10 (2) (1999) 402–409.
[35] A. Jain, A.K. Varshney, U.C. Joshi, Short-term water demand forecast modeling at IIT Kanpur using artificial neural networks, Water Resour. Manage. 15 (5) (2001) 299–321.
[36] A. Jain, L.E. Ormsbee, Evaluation of short-term water demand forecast modeling techniques: conventional v/s artificial intelligence, J. Am. Water Works Assoc. 94 (7) (2002) 64–72.
[37] A. Jain, S.K.V.P. Indurthy, Comparative analysis of event based rainfall–runoff modeling techniques—deterministic, statistical, and artificial neural networks, J. Hydrol. Eng. ASCE 8 (2) (2003) 93–98.
[38] P. Coulibaly, F. Anctil, B. Bobee, Multivariate reservoir inflow forecasting using temporal neural networks, J. Hydrol. Eng. ASCE 6 (5) (2001) 367–376.
[39] J.D. Salas, J.W. Delleur, V. Yevjevich, W.L. Lane, Applied Modeling of Hydrologic Time Series, Water Resources Publications, Littleton, CO, USA, 1997.
[40] D.E. Rumelhart, G.E. Hinton, R.J. Williams, Learning representations by back-propagating errors, Nature 323 (1986) 533–536.
[41] A. Jain, L.E. Ormsbee, An evaluation of the available techniques for estimating missing fecal coliform data, J. Am. Water Resour. Assoc. 40 (6) (2004) 1617–1630.
[42] A. Jain, A. Kumar, An evaluation of artificial neural network technique for the determination of infiltration model parameters, J. Appl. Soft Comput. 6 (3) (2006) 272–282.
[43] S. Srinivasulu, A. Jain, A comparative analysis of training methods for artificial neural network rainfall–runoff modeling, J. Appl. Soft Comput. 6 (3) (2006) 295–306.