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Neural Network Model for Nile River Inflow Forecasting Based on Correlation Analysis of Historical Inflow Data

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Abstract: Developing river inflow forecast is an essential requirement for reservoir operation. Accurate forecasting results in better control of water availability, more refined operation of reservoirs and improved hydropower generation. Artificial Neural Networks (ANN) models have been determined useful and efficient, particularly in problems for which the characteristics of the processes are difficult to describe using mathematical models. The ANN forecasting model is established considering the utilization of the inflow pattern of the previous three months. In this study, real inflow data collected over the last 130 years at Lake Nasser upstream Aswan High Dam (AHD) on Nile River, Egypt was used to develop and examine the performance of the proposed method. The results showed that the proposed ANN model was capable of providing monthly inflow forecasting with Relative Error (RE) less than 20%, which is considerably more accurate if compared with the pre-developed regression model. The main merit of this model is to provide accurate source of information for inflow forecasting for better reservoir operation and appropriate long-term water resources management and planning.

Key words: Inflow forecasting, reservoir operation, artificial neural network, correlation analysis

INTRODUCTION

The Aswan's High Dam (AHD), which is a major irrigation structure in Egypt, is located on the Nile River near the city of Aswan. With the completion of the AHD in 1970, a heuristic operation was established and adopted for the management and operation of the AHD reservoir. Its reservoir namely, Lake Nasser is considered as the largest man made lake allover the world. Lake Nasser is supplied by Nile River flow with an average annual inflow of 84 billion cubic meters (BCM). The reservoir supplies water for irrigation, municipal and industrial and energy production as well as navigation purposes. Water allocations to these groups of users are prioritized, with the highest priority given to irrigation.

Developing optimal release policies of multi-purpose reservoirs is very complex, especially for reservoirs with explicit stochastic environment (e.g., uncertainty in future inflows). The development of management models for identification of optimal operating policies for reservoirs spans over four decades of research. In a random environment, where climatic factors such as stream flow are stochastic, the economic returns from reservoir releases defined by the optimal policy are uncertain. Furthermore, the consequences of release decision cannot be fully realized until future unknown (inflow) events occur.

Operation policy of the reservoir is based on dividing Lake Nasser storage into six zones, as shown in Fig. 1. The dead storage zone, that is allocated to receive sediments coming with the river flow during the flood period, has a top elevation of 147 m with total volume of about 31 BCM. The operation rule for this zone is to release no flow regardless of the downstream requirements. The second zone is the live storage zone, which amounts to 90 BCM. This zone is divided into two parts. The first part is called buffer part that lies between elevation 147 m and elevation 150 m. Within this zone, the dam operators make their releases to meet the downstream requirements. The total annual release should not overshoot Egypt's quota (55.5 BCM). The remaining storage between elevations 175 and 183 m is divided between a flood buffer and flood control zone. Although the emergency spillways are designed to have a crest level of 178 m, it is decided to control the reservoir releases so that the water elevation does not exceed 175 m at the end of the hydrologic year (July 31st). As shown in Fig. 1, the level of 178 m is separating the flood

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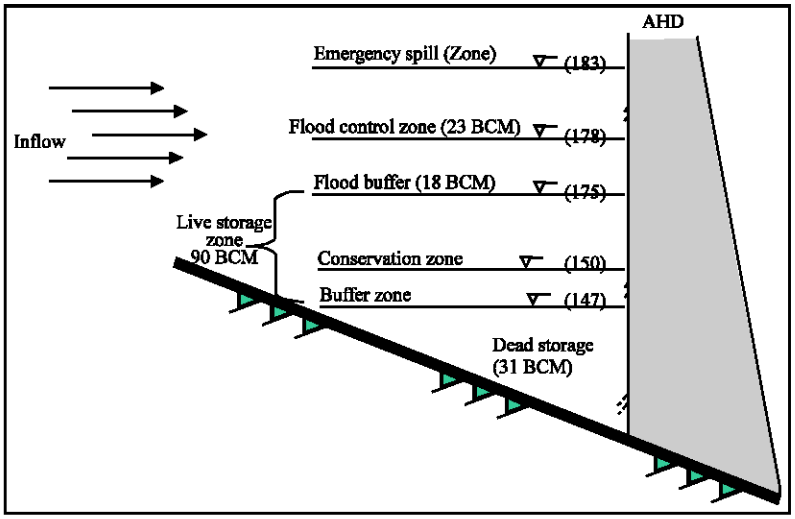

Fig. 1: Main components for different operation zones of AHD reservoir

buffer zone from the flood control zone at which any accumulated volume has to be spilled (Fahmy, 2001; Sadek *et al*., 1997).

As a result, river flow forecasts become an essential requirement for AHD reservoir operation. Accurate forecasting means better control of water availability, more refined operation of reservoirs and improved hydropower generation. Therefore, the problem of forecasting of natural Nile River flows is of considerable importance and new inflow forecasting models should be investigated.

River flow is believed to be highly nonlinear, time-varying, spatially distributed and not easily described by simple models. Two major approaches for modeling the river flow forecasting process have been explored in the literature. These are the conceptual (physical) models and the system-theoretic models. Conceptual river flow forecasting models are designed to approximate within their structures (in some physically realistic manner) the general internal sub-processes and physical mechanisms, which govern the hydrologic cycle. These models usually incorporate simplified forms of physical laws and are generally nonlinear, time-invariant and deterministic, with parameters that are representative of river flow characteristics. Until recently, for practical reasons (data availability, calibration problems, etc.) most conceptual river flow-forecasting model assumed lumped representations of the parameters. While such models ignore the spatially distributed, time-varying and stochastic properties of the river flow process; they attempt to incorporate realistic representations of the major non-linearities inherent in the river flow and climatic parameters relationships. Conceptual river flow models are generally reported to be reliable in forecasting the most important features of the hydrograph, such as the beginning of the rising limb, the time and the height of the peak and volume of flow. However, the implementation and calibration of such model can typically encounter various difficulties including sophisticated mathematical tools, significant amounts of calibration and some degree of experience with the model.

While conceptual models are of importance in the understanding of hydrologic processes, there are many practical situations such as river flow forecasting where the main concern is with making accurate predictions at specific locations. In such a situation, it is preferable to develop and implement a simpler system-theoretic model instead of developing a conceptual model. In the system-theoretic approach, models based on differential equations (or difference equations in case of discrete-time systems) are used to identify a direct mapping between the inputs and outputs without detailed consideration of the internal structure of the physical processes. The linear time-series models such as ARMAX (Auto Regressive Moving Average with exogenous inputs) models developed by Box *et al.* (1994) have been usually used in such situations because they are relatively easy to develop and implement. They have been determined to provide satisfactory predictions in many applications (Bras and Rodriguez-Iturbe, 1993). However, such models do not attempt to represent the nonlinear dynamics inherent in the river streamflow and therefore may not always perform adequately.

Motivated by the difficulties associated with nonlinear models, their complex structure and parameter estimation techniques some truly nonlinear system-theoretic river flow forecasting models have been reported. In most cases, linearity or piece-wise linearity has been assumed (Chetan and Sudheer, 2006). Allowing the model parameters to vary with time can compensate for the model structural errors that arise from such assumptions. For example, real-time identification techniques, such as recursive least squares and state-space Kalman filtering, have been applied for adaptive estimation of model parameters (Bras and Rodriguez-Iturbe, 1993).

Recently, significant progress in the fields of nonlinear pattern recognition and system control theory has made advances in a branch of nonlinear system theoretic modeling called Artificial Neural Networks (ANN). An ANN is a nonlinear mathematical structure, which is capable of representing arbitrarily complex nonlinear processes that relate the inputs and outputs of any system. ANN models have been used successfully to model complex nonlinear input-output time series relationships in a wide variety of fields.

The success with which ANNs have been used to model dynamic systems in other fields of science and engineering suggests that the ANN approach may prove to be an effective and efficient way to model the river flow process in situations where explicit knowledge of the internal hydrologic sub-process is not required. Some studies in which ANN models have been applied to problems involving river watershed and weather prediction have been reported in the literature. French *et al*. (1992) demonstrated that an ANN is capable of forecasting the complex temporal and spatial distribution of rainfall generated by a rainfall simulation model. Chang and Tsang (1992) used an ANN to model Snow Water Equivalent (SWE) from multi-channel brightness temperatures and obtained better results than a multiple regression model.

A wide range of application of ANN technique has been investigated in the field of water resources management specially for river flow forecasting. Chetan and Sudheer (2006) developed a hybrid linear-neural model for forecasting the river flow of Kolar basin, in India. Eiji *et al*. (2003) proposed a method for inflow forecasting of the Karogawa Dam by using neural networks. The methodology was applied using the rain data outside and inside the dam basin. The model reduced the forecasting error by about 30%.

Coulibaly *et al*. (1999, 2000, 2001a, b) reported that Recurrent Neural Network (RNN) could be appropriately utilized for inflow forecasting while taking into consideration the precipitation, snowmelt and temperature. However, it was reported that complex training procedure as well as long training time is required to achieve the desired performance.

Apparently, the nonlinear ANN model approach is shown to provide better representation of inflow forecasting than other conventional methods. Because the ANN approach presented here does not provide models that have physically realistic components and parameters, it is by no means a substitute for conceptual river flow forecasting modeling. However, the ANN approach does provide a variable and effective alternative to the traditional approach for developing input-output forecasting models in situations that do not require modeling of the other physical parameter of the river flow.

For more than thirty-four years of operation of the AHD and Lake Nasser reservoir, the inflow to the lake faces different cycles (flood and drought). Accordingly, several efforts have been made for developing forecasting models of the natural inflow at AHD. In fact, the nature of the Nile River inflow can be described as a multivariate process. Physically, the flow at a given station depends on the past and present flow rates at the upstream stations. However, it is extremely difficult at the present time to obtain accurate information about the flow rates at the upstream stations. Thus, a model completely based on the historical inflow data at the AHD is required. Fortunately, accurate inflow data at the AHD over the past 130 years are available. Information about the flow rates at the upstream stations as well as the climatic condition affecting the inflow are all embedded in this data.

Several forecasting models were suggested and developed using the uni-variate autoregressive moving average representation of the natural inflow at AHD (Salem and Dorrah, 1982; Koutsoyiannis *et al*., 2008). The results of these models tend to either over-estimated for low floods or under-estimated for high flood. This drawback is very vital to the feasible storage level to ensure that the storage limits, namely the dead storage and the reservoir capacity, are not violated. Therefore, it is essential to develop a model capable of mimicking the behavior of the River Nile inflow to produce forecasting sequences of the natural inflow at AHD.

The objective of this research is to analyze the historical inflow data of AHD and to develop an independent forecasting model of the natural Nile River inflow at AHD using ANN. While such a model is not intended as a substitute for a physiographic and hydro-climatology based models, it can provide a valuable alternative when the decision-maker of the AHD and Lake Nasser requires an accurate forecast of Nile River inflow to be provided using only the available input and output time series data. The anticipated impact of this model is that it can forecast the natural inflow at AHD without the need to explicitly represent the internal hydrologic or climatic parameters.

MATERIALS AND METHODS

Artificial neural networks: Artificial Neural Networks (ANN) is densely interconnected processing units that utilize parallel computation algorithms. ANN is also known as connectionism, parallel distributed processing, neuro-computing, natural intelligent systems and machine learning algorithms. The basic advantage of ANN is that they can learn from representative examples without providing special programming modules to simulate special patterns in the data set (Bishop, 1995). This allows ANN to learn and adapt to a continuously changing environment. While ANN do not provide a closed form mathematical model for the problem, they do offer accurate models based on the learning procedure. Neural Networks (NN) are composed of simple elements operating in parallel. These elements are inspired by biological nervous system and the network functionality is determined by the connections between them. The NN can be trained to perform a particular function by tuning the values of the weights (connections) between these elements. The training procedure of NN is performed so that a particular input leads to a certain target output as shown in Fig. 2.

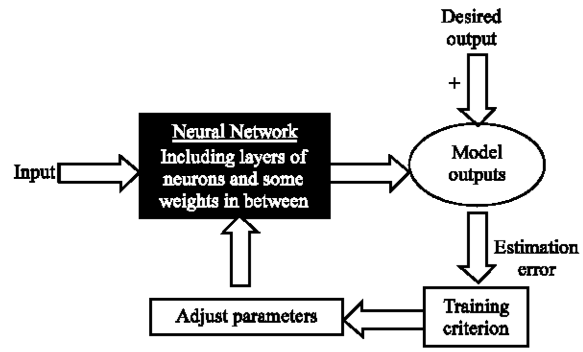

Fig. 2: Artificial neural network model

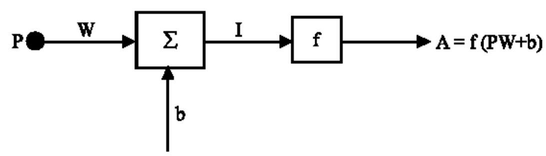

Fig. 3: The neuron model

The neurons: ANN are networks of many simple processors (neurons) operating in parallel, each possibly having a small amount of local memory. The smallest network unit (the neuron) receives its input through a connection that multiplies its strength by a scalar weight w and adds a bias b. The sum of the weighted inputs and their weights and biases is the argument for a transfer function f that produces the neuron output a. Figure 3 shows a schematic model for a single neuron. A neural network can consist of an input layer, an output layer and a number of hidden layers that might have variable number of neurons each. The pattern of connectivity in the network is represented by a weight vector W. The pattern of connectivity (excitatory or inhibitory) characterizes the architecture of the network (Ripley, 1996). By adjusting the connections weights (W) and the biases (b) the network can exhibit any desired output. The process of adjusting the weights and the biases of the network is known as the training process. In other words, an ANN learns from examples (of known input/output sequences) and exhibits some capability for generalization beyond the training data (Bishop, 1995; Ripley, 1996; Tsoukalas and Uhrig, 1997).

Transfer functions: Transfer functions for the neurons are needed to introduce non-linearity into the network. Bounded activation functions such as the logistic are particularly useful when the target values have a bounded range. But if the target values have non-bounded ranges, it is preferable to use an unbounded activation function. Many transfer functions have been introduced by ANN researchers. Commonly used transfer functions include hard limit transfer functions that are used in perceptron networks (Gibson and Cowan, 1990), linear, sigmoid and log-sigmoid transfer functions that are used in feedforward networks. The linear and the log-sigmoid transfer functions are further described below as they are used in the networks:

- **Linear transfer function:** Neurons utilizing this transfer function are usually utilized as linear approximates in adaptive linear filtering (Tsoukalas and Uhrig, 1997).
- **The log-sigmoid transfer function:** This transfer function has an output ranging between 0 and 1. This transfer function is commonly used in backpropagation networks, in part because it is differentiable (Bishop, 1995).

Multi-layer networks: Multi-layer networks are powerful modeling tools (Bishop, 1995; Ripley, 1996). The input and the output layers of any network have numbers of neurons equal to the number of the inputs and outputs of the system respectively. The layers between the input and the output layers are known as hidden layers. The number of neurons and hidden layers can be arbitrarily chosen and adjusted until the function can map the desired output. It has been proven that a network of two layers that utilizes a sigmoid and a linear transfer functions in its first and second layer respectively can be trained to model any non-linear relation (Bishop, 1995; Ripley, 1996).

Learning rules: The learning rule is a procedure for modifying the weights and biases of the network. This procedure may also be referred to as the training algorithm. Learning rules fall into two broad categories: supervised learning and unsupervised learning. In supervised learning, the learning rule is provided with a known input/output set of data and an algorithm is then used to adjust the weights and biases of the network in order to move the network outputs closer to the targets. Therefore, modelling capabilities of networks trained using supervised learning algorithms are limited to the range of the input used in training the network. In unsupervised learning the weights and biases of the network are modified according to the inputs only. Unsupervised learning is usually used to for data partitioning (Ripley, 1996; Tsoukalas and Uhrig, 1997).

Backpropagation algorithm: Bakpropagation is a generalized learning rule that is based on gradient descent algorithm and is commonly used with multi-layer networks that utilize non-linear transfer functions. The total weighted input at any neuron x_j and its output activity y_j based on a selected transfer function is computed. To perform the backpropagation learning rule, the network performs the following steps (Magoulas *et al*., 1999).

- Compute the Mean Square Error (MSE) between the output activity y_j and the desired output d_j over the whole range of data (N) as in Eq. 1:

$$\text{MSE} = \frac{1}{N}\sum_{i=1}^{N}\left(y_j - d_j\right)^2 \qquad (1)$$

- Compute the rate of change of the error E with respect to an output activity (y_j) represented by $\partial E/\partial y_j$. This derivative is the difference between the actual and the desired output (y_j-d_j)
- Compute the rate of change of the error E with respect to the input received by an output unit (x_j) represented by $\partial E/\partial x_j$
- Compute the rate of change of the error E with respect to the weight on the connection into an output unit (W_{ij}) represented by $\partial E/\partial W_{ij}$
- Compute the rate of change of the error E with respect to the activity of a unit in the previous layer (y_i) represented by $\partial E/\partial y_j$. This step allows backpropagation to be applied to multilayer networks

By repeating steps 1 to 5 the vectors of weights (W) and biases (b) can be altered to allow the network achieving the desired output. The simplest approach for updating the network weights and biases is described as:

$$W_{k+1} = W_k - \mu_k g_k \qquad (2)$$

where, μ_k is the learning coefficient which is a small positive constant that controls the step size of the iterative changes in the network weights and g_k is the error gradient vector.

Inflow forecasting with MLP-NN: In fact, the forecasting procedure is, by definition, an operation through which the future water inflow pattern can be provided. Most of present inflows forecasting systems attempt to forecast the inflow at monthly basis (Olason *et al*., 1997; Abrahart *et al*., 2007). However, the same theory can be applied to any kind of other timely basis (hourly, daily, weekly,... etc.) based on the nature of the data available. In this study, it is required to forecast the inflow at month t using the monitored inflow of some previous months. The number of months used to provide accurate inflow forecasting at certain month is based on data analysis and the desired accuracy. In addition, the inflow forecasted at month t can be used with the monitored inflow of some previous months to provide a forecasting at month t+1. This procedure of using the forecasted inflow can be repeated for L months and the value of L depends on the environmental conditions and the basin characteristics (Todd *et al*., 1999). It has been reported by Sutcliffe and Parks (1999) that the lead time L cannot be more than 3 months.

We have determined that inflow forecasting at certain month t based on the monitored inflow from the previous years at the same month (instead of previous months at the same year) cannot provide reliable results. This will be justified later by analysis of autocorrelation sequences of the inflow data at certain month t over number of years.

In this study, ANN with its nonlinear and stochastic modeling capabilities is utilized to develop a forecasting model that mimics the inflow pattern at AHD and predict the inflow pattern for two months ahead based upon the monitored/forecasted inflow at three previous months. The inflow Q_f forecasted at month t based on the inflow monitored Q_m at the previous three months can be expressed as:

$$Q_f(t) = f\left(Q_m(t-1), Q_m(t-2), Q_m(t-3)\right) \qquad (3)$$

Consequently, the inflow for month t+1 can be forecasted as follows:

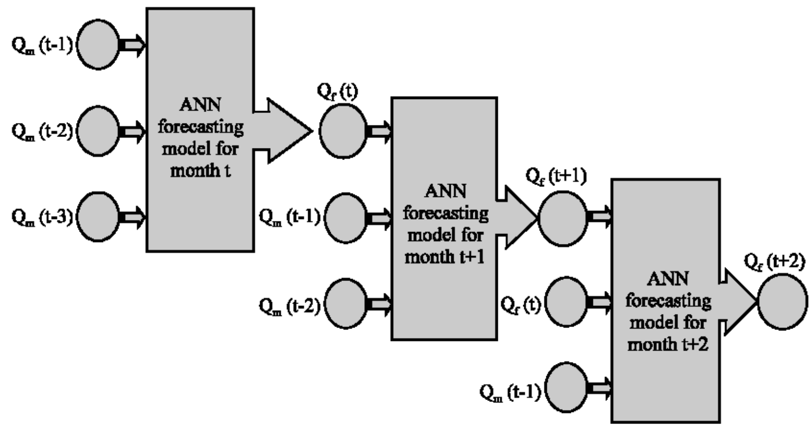

Fig. 4: Schematic representation of the proposed inflow forecasting procedure

Table 1: The ANN architecture for each month

Months	R	N_1	N_2	N_3	Transfer function	Transfer function	Transfer function
August	3	6	4	2	Log_sigmoid	Tan_sigmois	Pure-line
September	3	6	4	1	Log_sigmoid	Tan_sigmois	Pure-line
October	3	5	3	2	Log_sigmoid	Log_sigmoid	Pure-line
November	3	5	3	2	Log_sigmoid	Log_sigmoid	Pure-line
December	3	6	3	1	Log_sigmoid	Tan_sigmois	Pure-line
January	2	6	2	1	Log_sigmoid	Pure-line	____
February	2	4	3	1	Log_sigmoid	Pure-line	____
March	2	4	3	1	Log_sigmoid	Pure-line	____
April	2	6	4	1	Log_sigmoid	Pure-line	____
May	2	6	4	2	Log_sigmoid	Pure-line	____
June	3	5	4	2	Log_sigmoid	Tan_sigmois	Pure-line
July	3	5	4	2	Log_sigmoid	Tan_sigmois	Pure-line

$$Q_f(t+1) = f\left(Q_f(t), Q_m(t-1), Q_m(t-2)\right) \tag{4}$$

Similarly, the inflow for month t+2 can be forecasted using the following equation:

$$Q_f(t+2) = f\left(Q_f(t+1), Q_f(t), Q_m(t-1)\right) \tag{5}$$

In fact, Q_f in all of the above equations represents forecasted inflow while Q_m is a monitored inflow. The above procedure, which was applied at month t, can be repeatedly applied at every other month using the same model described in Eq. 3-5. A schematic representation of the above procedure is given in Fig. 4.

The ANN model is established using the above three equations. The architecture of the network consists of an input layer of three neurons (corresponding to the monitored/forecasted inflow of the previous three months at the inputs to the network), an output layer of one neuron (corresponding to the forecasted inflow) and number of hidden layers of arbitrary number of neurons at each layer. In order to achieve the desirable forecasting accuracy, 12 ANN architectures were developed (one for each month). Monthly natural inflows for the period of 60 years (between 1871 and 1930) were utilized to train the 12 networks. The performance and the reliability of the ANN model were examined using the inflow data monitored between 1931 and 1960. The capabilities of the developed ANN model was further verified by the inflow data between 1961 and 2000 that correspond to the inflow monitored after the construction of AHD in 1960.

In order to accelerate the training procedure and to achieve minimum mean square estimation error, the inflow data was normalized. Different MLP-ANN architectures (while keeping three neurons in the input layer and only one neuron in the output layer) were used to examine the best performance. The choice of the number of hidden layers and the number of neurons in each layer is based on two performance indices. The first is the root mean square value of the prediction error and the second is the value of the maximum error. Both indices are obtained while examining the ANN model with the inflow data between 1931 and 1960. The last group of data (between 1961 and 2000) verified the capabilities of the ANN model as it will be explained later in the results section. An example of the ANN architecture used for the month of August is given in Fig. 5.

The number of hidden layers (R) and the number of neurons in each layer (N) for each network are given in Table 1. The transfer functions used in each layer of the networks were also shown in Table 1. All 12 networks

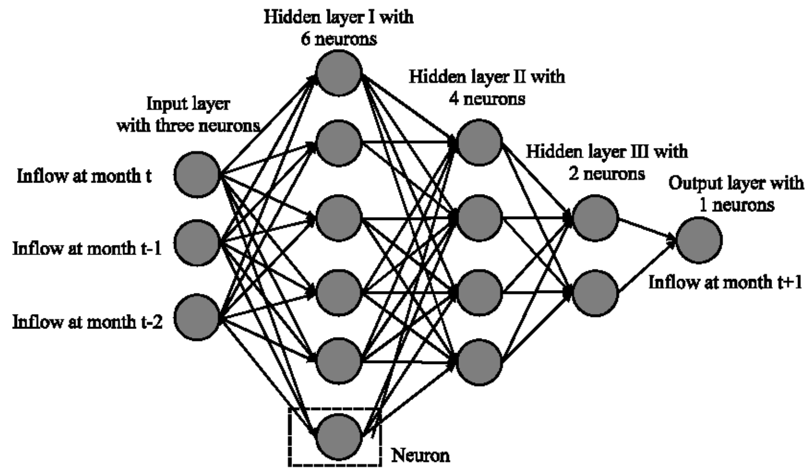

Fig. 5: The exact neural network architecture for month August

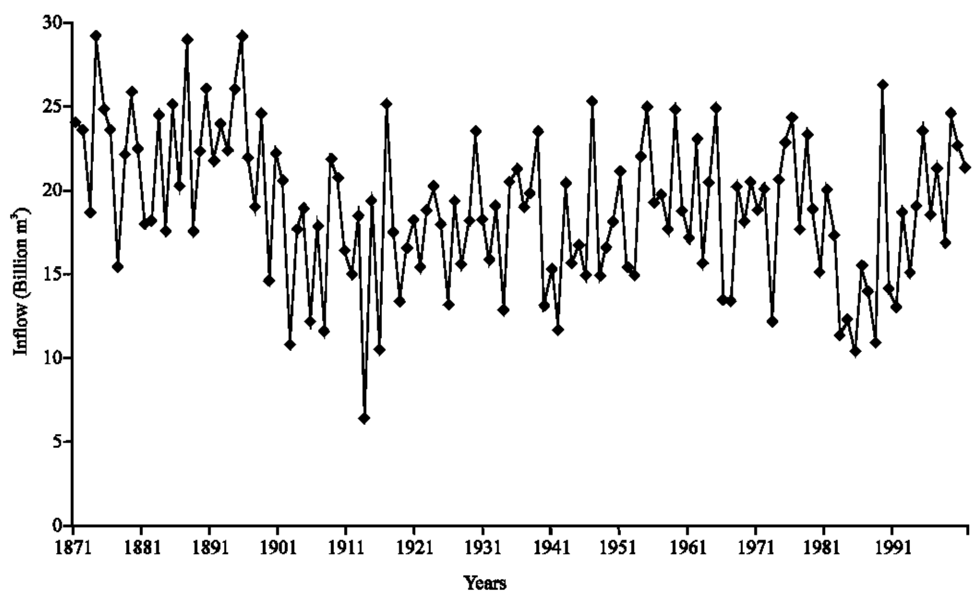

Fig. 6: The natural inflow at Aswan for period 1871-2000 for month August

utilize the backpropagation algorithm during the training procedure. The scaled conjugate gradient criterion was used to update the ANN parameters while training since it was reported that this method is the most suitable in case of high randomness on the input data, which is the case in this study (Chiang *et al*., 2004). This criterion is based on the conjugate gradient method but with small modification that avoid time consuming in the line search (Bishop, 1995).

Data analysis: In this study, the Nile River inflow data in Aswan published by the Egyptian Ministry of Water Resources and Irrigation was utilized. The inflows in Aswan for the period between 1871 and 1902 have been deduced using a general stage-discharge table, which has been constructed from the Aswan downstream gauge. Due to the construction of several dams and other hydraulic structures in Egypt and Sudan, the natural inflow from 1902 onwards have been derived directly from the general stage-discharge relationship in Aswan by correcting the measured inflow for the effect of losses from upstream reservoirs, abstractions in Sudan and the effect of regulation by Sennar Reservoir.

The natural inflows in Aswan for months August and March are demonstrated in the Fig. 6 and 7. Obviously, the monitored inflow is random in nature. Accordingly, it is recommended to analyze the data by studying the auto-correlation sequences for each month over the 130 years and the cross-correlation between consequent months in

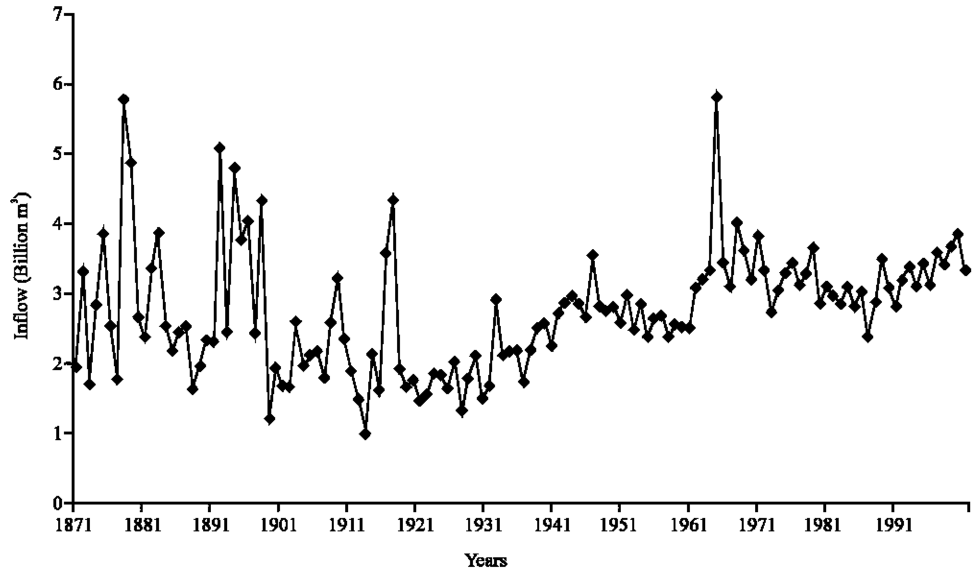

Fig. 7: The natural inflow at Aswan for period 1871-2000 for month March

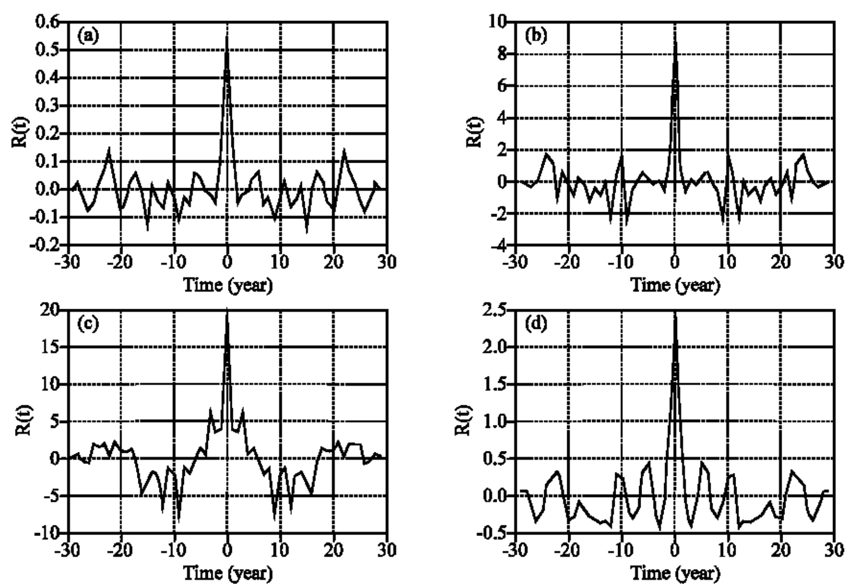

Fig. 8: The auto-correlation sequence for the inflow for months of (a) August, (b) September, (c) October and (d) November

the same year. The study of the auto-correlation function, clearly, tells how the process is correlated with itself over time. While studying the cross-correlation sequences provides information about the mutual correlation between two consequent months.

The auto-correlation sequence for a random process x(t), corresponding to a monitored inflow at certain month, is defined as:

$$R_{x(t)}(t) = E(x(t)\, x(t+t)) \tag{6}$$

where, τ is the independent time variable of the autocorrelation sequence R(τ).

On the other hand, the cross-correlation sequence (CCS) between the processes x(t) and y(t), corresponding to inflows at two consequent months, is defined as:

$$CCS(t) = E(x(t)\, y(t+t)) \tag{7}$$

Figure 8 shows the auto-correlation sequence for 4 different months with respect to time over 130 years.

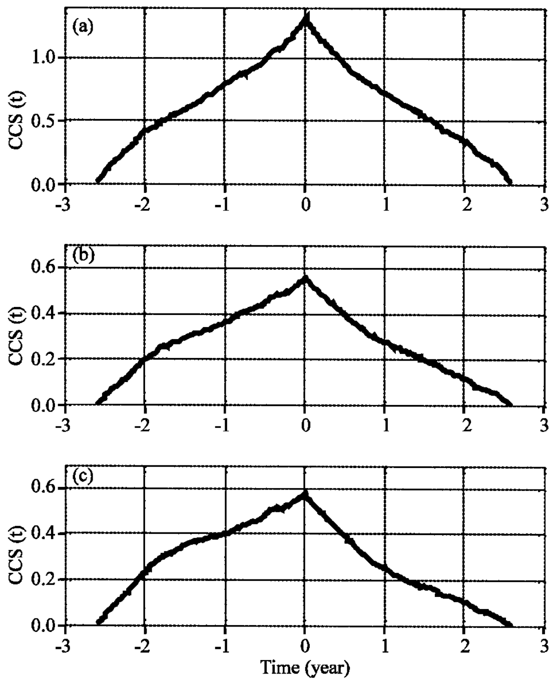

Fig. 9: The cross-correlation sequence for the inflow for months of (a) August-July, (b) August-June and (c) August-May

Obviously, these auto-correlation sequences decrease rapidly with respect to time showing no enough correlation over time. In this case, the auto-correlation function is more likely to represent a white sequence which is impossible to predict over time. In other words, it is unlikely to use neural networks to predict the inflow of certain month at certain year utilizing the monitored/forecasted inflow of the same month at the previous years.

Fortunately, studying the cross-correlation between the inflow at month t(Q(t)) and the inflow at three previous months (Q(t), Q(t−1), Q(t−2)) showed a strong correlation over time. Figure 9 shows the cross-correlation function between August and the previous three months (July-June-May). This justifies the architecture proposed in this study to predict the inflow at certain month based on the monitored/forecasted inflow at previous months shown in Fig. 4.

RESULTS AND DISCUSSION

The ANN-based architecture of Fig. 4 and 5 is employed in this study to provide inflow forecasting at each month. The monitored inflow over 60 years between 1871 and 1930 was used to train 12 networks with each network corresponds to one month. All 12 networks successfully achieved the target MSE. For example, the training curve for the month of August is demonstrated on Fig. 10 showing convergence to the target MSE of 0.0001 after 528 iterations.

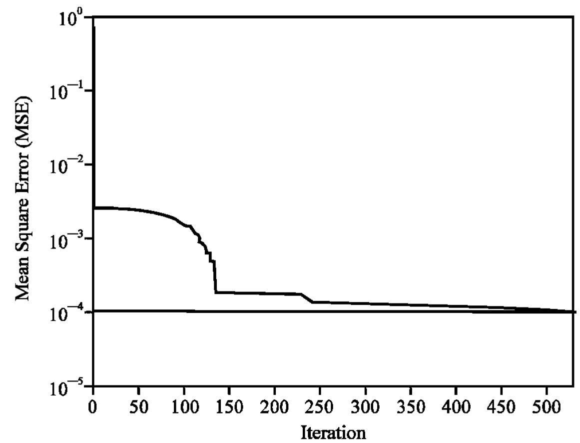

Fig. 10: Training curve for the month of August

Table 2: RMSE error associated with NN forecasting model for each month

Months	RMSE (BCM)	Maximum inflow (BCM)	Minimum inflow (BCM)
August	0.4900	29.10	6.50
September	0.7805	32.79	7.31
October	1.0689	27.40	5.97
November	0.1801	14.40	4.12
December	0.2838	11.00	2.83
January	0.2347	7.70	1.72
February	0.2282	6.04	1.15
March	0.0909	5.81	1.07
April	0.2389	5.26	0.95
May	0.3215	4.72	0.80
June	0.2665	5.16	0.90
July	0.5544	11.03	1.74

The 12 networks developed during the training procedure are used to provide the inflow forecasting for the next 30 years between 1931 and 1960. Since the inflow was accurately monitored over these 30 years, the performance of the proposed ANN-based architecture can be examined and evaluated. The distribution of the percentage value of the error over these 30 years as well as its RMSE value are the two statistical performance indices used to evaluate the model accuracy. The distribution of the percentage error between the monitored (actual) and the forecasted inflows over the 30 years between 1931 and 1960 is shown in Fig. 11 for 4 different months. Apparently, the highest percentage errors for these 4 months exist at the month of August, December, January and June and it is equal to 7%. However, we have determined that in some odd cases (for the months of October, February, April, May and July) the percentage error may take higher than normal values of approximately 18% as can be shown in Fig. 12.

Table 2 shows the RMSE value of the error over the same 30 years for the different months. Small RMSE values of the errors associated with the months of

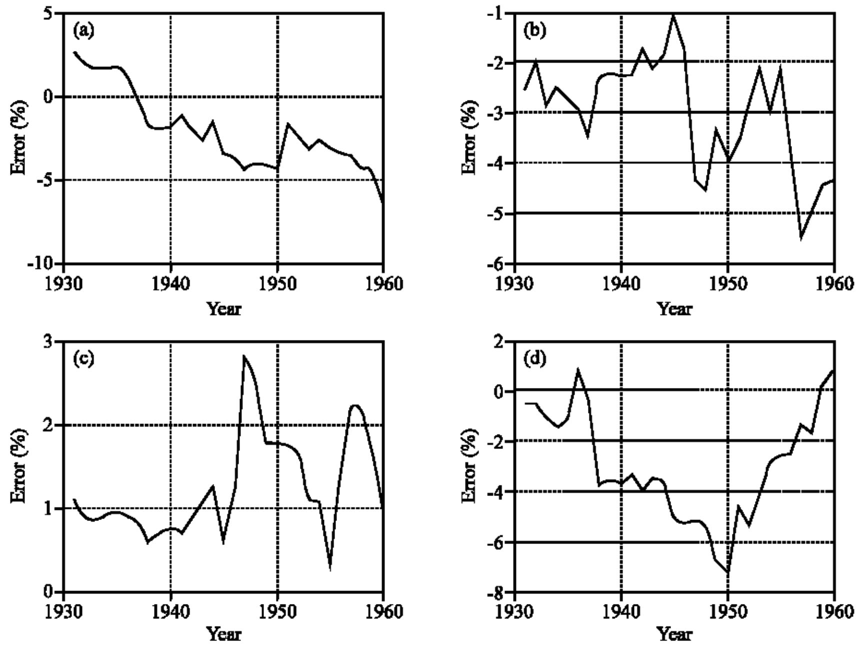

Fig. 11: The error distribution for (a) August, (b) December, (c) January and (d) June

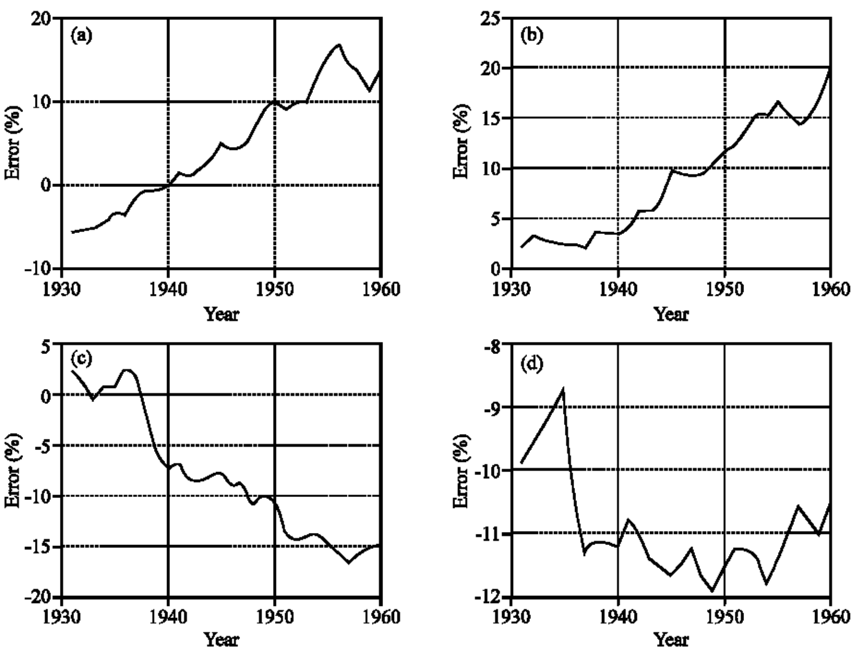

Fig. 12: The error distribution for (a) October, (b) February, (c) May and (d) July

(August, September, December and June) can be observed. This agrees with the small percentage errors shown in Fig. 11. Although the RMSE values of the errors associated with the months of (February and May) may look small, they correspond to relatively small values of the monitored inflow. For example, RMSE error values of 1.0689 BCM and 0.2282 BCM have been evaluated for the months of October and February, respectively. These values of RMSE errors are relatively high since they correspond to monitored inflow range of (27.40-5.97) BCM for October and (6.04-1.15) BCM for February. On the other hand, RMSE error values of 0.49 BCM and 0.0909 BCM have been evaluated for the months of August and March, respectively. These values of RMSE errors are

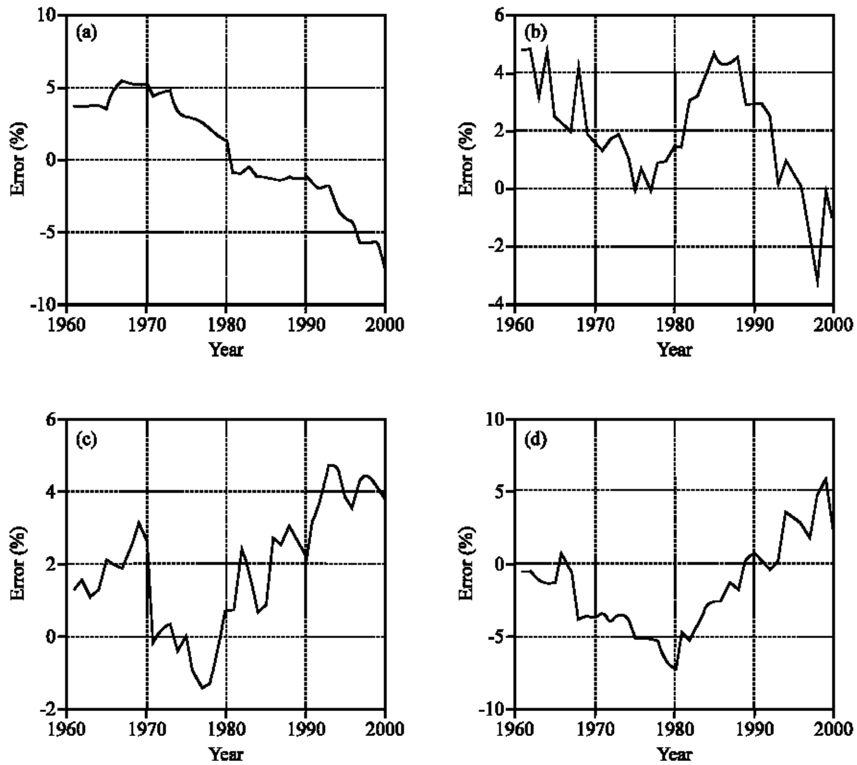

Fig. 13: Error distribution for months of (a) July, (b) June, (c) May and (d) March

small and correspond to monitored inflow range of (29.10-6.50) BCM for August and (5.81-1.07) BCM for March. After comprehensive analysis of the relatively high percentage errors at the months of October, February, April, May and July, we have figured out that an over-fitting problem may have occurred while training the corresponding networks. The over-fitting problem is simply that the network was trained to only memorize the training examples, but it did not learn to generalize.

More verification of the performance of the ANN-based inflow-forecasting model has been established using the inflow data between 1961 and 2000. Table 3 shows the RMSE value of the inflow error over these 40 years using the same 12 networks used between 1961 and 2000. Apparently, the same levels of errors have been achieved. In addition, Table 3 shows performance of the multi-lead forecasting for two months ahead as mentioned above. The second column shows the RMSE forecasting error when only the monitored inflows from the previous months are utilized at the input of the model. The third column corresponds to the case when one forecasted inflow and two monitored inflows are used at the network inputs while the fourth column corresponds to the case of two forecasted inflows and one monitored inflow are utilized. It can be depicted that the inflow forecasting accuracy is reduced when less monitored inflow is used at the network input. For example, the RMSE error for the inflow forecasted at the month of November was 0.1369 BCM when the monitored inflows of the months of August, September and October are used at the input. This error increases to 0.1441 BCM when the monitored inflows of August and September and the forecasted inflow of October are used. Furthermore, the RMSE error has further increased to 0.1561 BCM when the monitored inflow of August and the forecasted inflows of September and October are used.

Table 3: RMSE associated for NN forecasting model for period of (1961-2000) and the lead time for two months ahead

Months	RMSE (BCM) month (t)	RMSE (BCM) month (t+1)	RMSE (BCM) month (t+2)
August	0.4510	0.6966	0.8957
September	0.6385	0.8268	0.1561
October	0.7785	0.1441	0.3689
November	0.1369	0.3406	0.3051
December	0.3121	0.2816	0.2967
January	0.2640	0.2738	0.1182
February	0.2601	0.1091	0.1806
March	0.1027	0.1667	0.2238
April	0.1541	0.2066	0.3465
May	0.1996	0.3198	0.5011
June	0.2931	0.4625	0.6150
July	0.4432	0.5166	0.8127

Figure 13 shows the distribution of the errors for the months of July, June, May and March. It can be determined that the model is examined separately for these

Table 4: RE % associated with the output of the proposed ANN and ARMA models on monthly basis for years 1999 and 2000

	ANN		Conventional method ARMA (Salem and Dorrah, 1982)	
	Year		Year	
Month	1998-99	1999-2000	1998-99	1999-2000
August	14.70	16.19	-24.80	-27.57
September	11.79	-12.04	23.62	29.77
October	-16.38	-17.62	-22.49	32.15
November	15.76	-16.62	-21.42	-25.53
December	-15.26	14.54	27.60	35.07
January	6.08	9.01	-26.04	-35.43
February	11.91	15.96	31.64	35.78
March	2.80	2.60	29.26	-36.14
April	14.04	16.10	31.32	21.21
May	4.02	3.85	23.15	21.00
June	-0.52	-0.90	-24.31	-22.05
July	-7.10	-7.50	34.73	31.01

40 years (between 1961 and 2000). This is actually due to the significant change in the inflow pattern during the period between 1961 and 2000 that experienced different cycles of high flood and drought. However, the proposed ANN-based forecasting module that utilizes monitored/forecasted inflow of previous months to predict the inflow at the present month (and developed using inflow data between 1871 and 1930) is still performing adequately without change. This shows an important feature of the proposed model, which is established based on studying the autocorrelation and the cross-correlation sequences of the inflow data.

For further analysis of the proposed ANN model, Table 4 compares the performance of the NN to the ARMA models over the period between August 1998 and July 2000 (two water years) using the Relative Error (RE) % indicator for each month.

$$\text{RE }(\%) = 100 * \left(\frac{|Q_{f\,(\text{testing})} - Q_m|}{Q_m}\right) \quad (8)$$

where, $Q_{f\,(\text{testing})}$ is the forecasted inflow for a specific month and Q_m is the monitored inflow for this month. It is obvious from Table 4 that the NN model outperformed the ARMA models with remarkable improvements in the RE% for all months.

CONCLUSION

This study suggested a neural network based model for inflow forecasting which is established based on stochastic analysis of the historical records of inflow. This model does not necessitate incorporating the physical nature of the inflow, physiographic conditions, the lags of independent variables and other climatic conditions that are already embedded in the historical inflow records. Furthermore, multi-lead forecasting can be established using the same model. The proposed method was applied to provide inflow forecasting for Nile river flow at Lake Nasser in Aswan. Despite the highly stochastic nature of the inflow data in this region, the proposed model was capable of mimicking the inflow pattern accurately with relatively small inflow forecasting errors of less than 10%. Therefore, it is anticipated that significant improvement in reservoir operation and management can be achieved when integrating with the proposed forecasting model.

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