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Simulation of Hydropower Systems Operation using Artificial Neural Network

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Abstract—This paper presents a simulation model for hydropower systems. Reliability-Based Simulation (RBS) model is a common tip for simulation of Hydropower systems. This method is based on determination of power generation capacity using iteration process mentioned initial firm energy. Also, in this method energy equation is implicit and solving it requires the iteration process too. This method is time consuming especially in multi-reservoir systems. Using Artificial Neural Network (ANN) the desired parameter such as releases from reservoir can be obtained more quickly.

Index Terms—RBS model, Hydropower systems, Artificial Neural Network.

I. INTRODUCTION

The complexity and challenging issues arisen in the management of water resources have called for interdisciplinary collaboration of experts and development of hydro models. Hydro power plants play a key role in electric power systems, due to their low operating costs and their flexibility in real time operation. In addition, sustainability and environmental concerns support their use in current power systems, jointly with other renewable sources of energy, like wind and solar energy. Descriptive simulation models, due to their computational advantages, are able to consider more details of real systems than optimization models. However, they require that the model builder specifies an operating policy. Use of rule curves [5], heuristic rules such as space rule [2], New York City (NYC) rule [3], [4], hedging rules [7] are common ways of defining operating policies required in simulation models. [6] discuss the operating rules for hydropower systems in series and parallel. Reservoir simulations normally require large computational effort and considerable time consumption so that the activities connected with reservoir simulators suffer severe limitations that make it difficult with the vigorous development. Recently some techniques such as Spline, Kriging, Artificial Neural Networks, Experimental Design [8], [1], [9] have been proposed to minimize these problems. The successful applications of Artificial Neural Networks in several research fields suggest the investigation of appropriated architectures to be used as proxies to reservoir simulator. In this article RBS model do not use the iterative process which is so time consuming.

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The end of month reservoir storage and turbine releases determination requires changing steps that using artificial neural network these desired solutions can be obtained more quickly. Also, results of the researches related to investigation of different types of Neural

II. ARTIFICIAL NEURAL NETWORKS

Neural networks are composed of simple elements operating in parallel. These elements are inspired by biological nervous systems. As in nature, the network function is determined largely by the connections between elements. We can train a neural network to perform a particular function by adjusting the values of the connections (weights) between elements. Commonly neural networks are adjusted, or trained, so that a particular input leads to a specific target output. Such a situation is shown below. There, the network is adjusted, based on a comparison of the output and the target, until the network output matches the target. Typically many such input/target pairs are used, in this *supervised learning*, to train a network Networks as proxies to reservoir simulator are analyzed and Feed- Forward Back-Propagation Multilayered are selected.

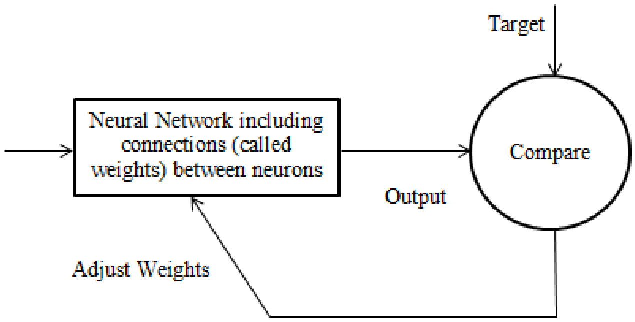

Fig.1 Schematic of Artificial Neural Network role

Batch training of a network proceeds by making weight and bias changes based on an entire set (batch) of input vectors. Incremental training changes the weights and biases of a network as needed after presentation of each individual input vector. Incremental training is sometimes referred to as “on line” or “adaptive” training. Neural networks have been trained to perform complex functions in various fields of application including pattern recognition, identification, classification, speech, vision and control systems. A list of applications is given in Chapter 1. Today neural networks can be trained to solve problems that are difficult for conventional computers or human beings. Throughout the toolbox emphasis is placed on neural network paradigms that build up to or are themselves used in engineering, financial and other practical applications.

Neural Networks have been successfully applied in several research fields of the petroleum engineering. From reservoir characterization to e-fields the Neural Networks have found a large number of applications. Amongst the most important Neural Networks is Feed- Forward Back-Propagation Multilayered. The versatility of this network makes it possible to use in the solution of several problems. The difficulty in the application of this Neural Network as proxy to reservoir simulator is that this Neural Network to be fully trained requires large quantity of reservoir simulations. On the other hand, the central aim for the development of proxies to reservoir simulators is an eventual, significant reduction of the number of reservoir simulations, so the application of the Feed-Forward Back-Propagation Multilayered in a first moment is not recommendable. In this article, Neural Networks which did not require a large number of reservoir simulations to be fully trained are used. These Neural Networks were trained with a reduced number of reservoir simulations and presented a high accuracy.

III. RELIABILITY- BASED SIMULATION

In this method Firm energy or Production capacity of reservoir are assumed. In the mass balance equation the end of month storage and reservoir release are unknown. In this step the end of month storage (average normal water level is a function of end of month storage) is assumed then using energy equation reservoir release is determined. This amount of release is set into mass balance equation and new end of month storage is obtained but some constraints should be considered for it. Maximum and minimum storages and maximum energy generated are the most important factors. If the final end of month storage is the same as initial end of storage, the process can go to next step. Equation 1 and 2 show mass balance and energy equations respectively.

$$S(t+1)=S(t)+I(t)-R(t) \tag{1}$$

Where $S(t+1)$= end of month storage, $S(t)$= start of month storage, $I(t)$= inflow to reservoir and $R(t)$= turbine release

$$R(t)=\frac{Icap\times nHours\times PF}{2.725\times\left(\bar{h}(t)-h_{Tail}-h_f\right)\times e_p} \tag{2}$$

Where Icap = power plant installed capacity; Hours=number of days per month; PF= plant factor specified by hours per day for which the power plant generates power with its production capacity; $\bar{h}(t)$ = average head of the month; h_{Tail} = tail-water level; h_f = total loss in channel and e_p = power plant efficiency. In equation 1, $\bar{h}(t)$ depends on the turbine release making the equation implicit with respect to R and this is the reason that iteration process is selected. If the end of month storage is bigger than maximum storage it means that, it reaches to maximum storage and the additional amount of water adds to turbine release and secondary energy is generated and system can generate production capacity but if the end of month storage is smaller than minimum storage it means that, it reaches to minimum storage and the turbine release decreases and system fails to generate the production capacity. If the end of month storage is between maximum and minimum storages the end of month storage and turbine release would not be changed and system can generate production capacity.

$$S_{Min}\le S(t+1)\le S_{Max}, Z=1 \tag{3}$$

$$S(t+1)>S_{Max}, Z=1 \tag{4}$$

$$S(t+1)<S_{Min}, Z=0 \tag{5}$$

The total numbers that system success to generate the production capacity to the number of months is defined as reliability. If reliability is more than desire reliability, production capacity should be increase and if it smaller than desire reliability, production capacity should be decreased until the target reliability is obtained. The RBS model is shown in the figure below.

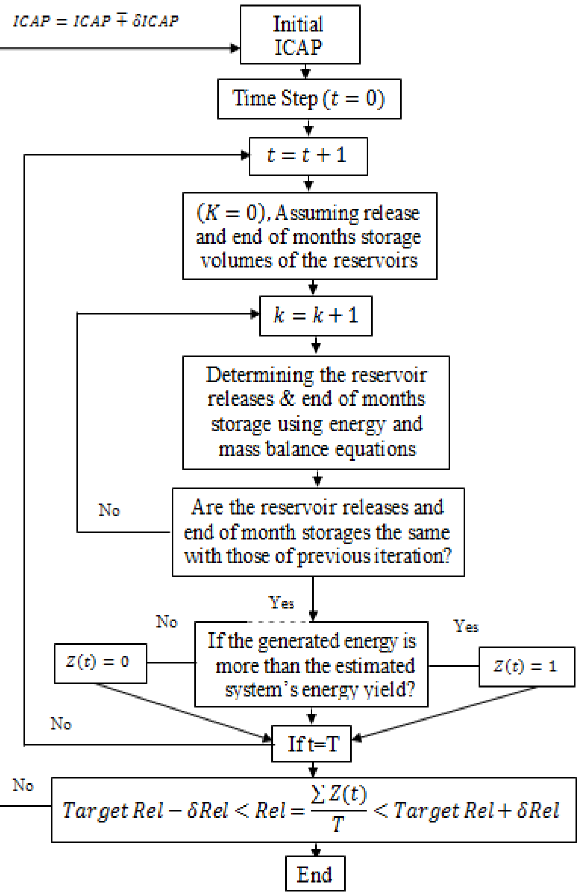

Fig.2 Single reservoir RBS model flowchart

The total numbers that system success to generate the production capacity to the number of months is defined as reliability. If reliability is more than desire reliability, production capacity should be increase and if it smaller than desire reliability, production capacity should be decreased until the target reliability is obtained.

IV. CASE STUDY

The dam is on the Karkheh River in the Northwestern province of Khozestan, the closest city being Andimeshk to the east. It is 127 metres (417 ft) high and has a reservoir capacity of 5.9 billion cubic meters. The Karkheh Dam is designed to irrigate 320,000 hectares of land, produce 520 MW of hydro-electricity and prevent downstream floods. This reservoir is constructed and the installed capacity is obtained. In this paper the Karkheh reservoir is analyzed and answers are checked with the real ones. Energy generation in Karkheh considered as secondary energy. In other word, energy generated from additional water releases to downstream of Karkheh basin. Upstream releases are regarded as inflows to Karkheh reservoir. Figure 4 shows the schematic of Karkheh reservoir. D1, D2 and D3 are agricultural, domestic and environmental demands. Table 1 shows the characteristics of Karkheh Reservoir.

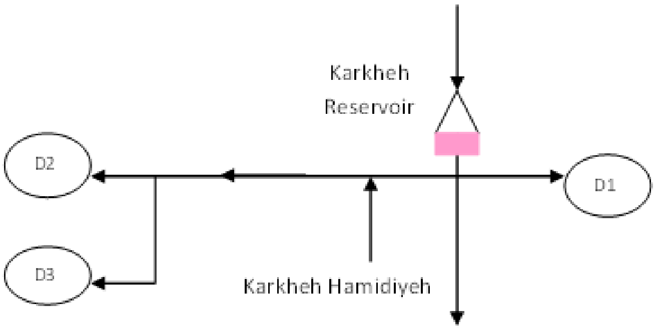

Fig.3 schematic of Karkheh reservoir

Table. 1 Characteristics of Karkheh reservoir

Characteristics	
Efficiency of the plant	0.925
Plant factor	0.25
Tailwater level (masl)	115
Head loss (m)	3
Target reliability	0.9
Target vulnerability	0.5

V. NEURAL- SIMULATION MODEL

In the RBS model iteration process in end of month storage is so time consuming and it requires a high- speed computer. Artificial Neural Network as a powerful regression model gets some inputs and by using a number of inner functions in the hidden layers, generates the outflows. In huge problem the best criteria for assessment of network is R^2. In this paper the inputs are included inflows to reservoir and storage volume of reservoir. On the other hand, turbine releases are the desired outputs. It should be mentioned that artificial neural networks do not guarantee the same simulation model answers but the errors in total should set the reliabilities and production capacities in a stable range with reasonable deviations. For this problem there are lots of inputs and output, so the two layer neural network is employed. In first one, function "logsig" generates outputs between 0 and 1 as the neuron's net input goes from negative to positive infinity.

Alternatively, multilayer networks may use the tan-sigmoid transfer function "tansig". Second layer uses the linear transfer function "purelin" is used in backpropagation networks. The normalized perceptron rule function "learnpn" takes slightly more time to execute, but reduces number of epochs considerably if there are outlier input vectors. In this modeling 100 epochs for 600 vector input and output is reasonable. The inputs including reservoir storage and inflows and outputs are turbine releases.

VI. RESULTS, CONCLUSION AND DISCUSSIONS

The model operated and ran for the Karkheh hydropower system to simulate it. The kind of artificial neural network selection requires the experience and try. The results are shown in following figure and table.

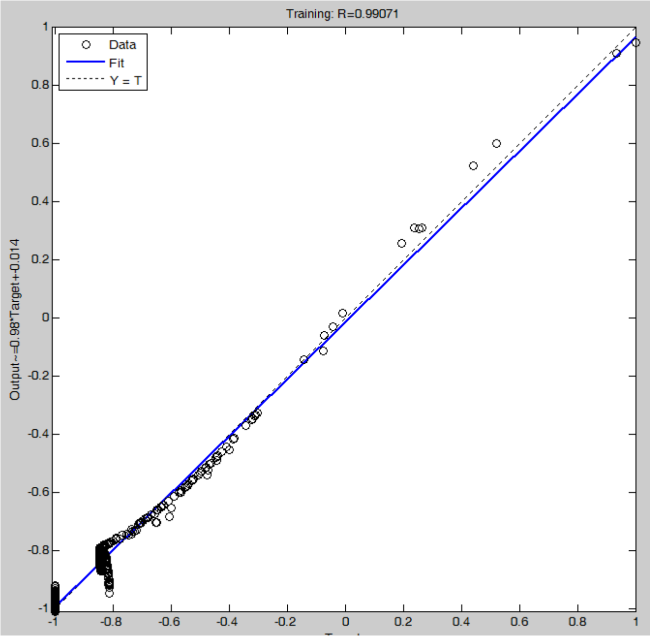

Fig.4 R index in training process

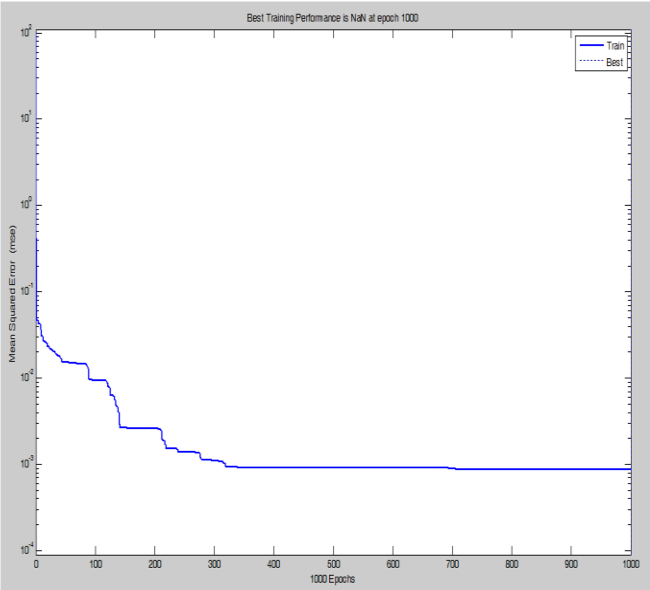

Fig.5 Best training performance

The above figures present that simulation model performs efficiently without iteration process. The other results which are obtained reasonable are shown in following table. The time of running for a production capacity is about 7 seconds while in the iterative process this time extremely depends on initial assumption but for a step which has a production capacity takes about 11 seconds. This method has more beneficial aspects in multi-reservoir systems which time plays a key role.

Table. 2 Results in RBS and Neural RBS models

Installed Capacity (RBS)	400 MW
Reliability (RBS)	0.88
Installed Capacity (ANN)	438 MW
Reliability (ANN)	0.83

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