Proceedings of
INTERNATIONAL CONFERENCE ON COMPUTING, COMMUNICATION AND ENERGY SYSTEMS (ICCCES-16)
In Association with IET, UK & Sponsored by TEQIP-II
29th -30th, Jan. 2016

Paper ID: CSEIT 22

A STUDY OF RECURRENT NEURAL NETWORKS BASED WATER LEVEL FORECASTING FOR FLOOD CONTROL: CASE STUDY ON KOYANA DAM

Mr. Avadhoot S. Idate
Computer Science and Technology Department of Technology, Shivaji University Kolhapur, India
Mrs.R.J. Deshmukh
Computer Science and Technology Department Of Technology, Shivaji University Kolhapur, India

Abstract- Flood control is crucial task that faces fatal hazards due to fast rising peak flows from urbanization. To lower down the future flood damages, it is imperative to construct an on-line accurate model to forecast inundation levels during flood periods. The regions near Koyna and Krishna basins located in Maharashtra region is selected as study area. In this approach first step is the analysis of historical hydrologic data by statistical techniques to identify the time span of rainfall affecting the rise of the water level in the floodwater storage pond (FSP) at the regions. Second step is the effective factors that affect the FSP water level are extracted by the Gamma test. Thirdly, one static artificial neural network (ANN) (Back Propagation Neural Network-BPNN) and two dynamic ANN's

(Elman Neural network-Elman NN; Nonlinear Autoregressive Network with Exogenous input-NARX network) are used to construct multi-step-ahead FSP water level forecast models through scenarios i.e rainfall and FSP water level forecast model inputs and only rainfall data as model inputs. This study suggests that the proposed NARX models can be valuable and beneficial to the government authority for urban flood control.

Keywords- Artificial neural networks (ANNs), nonlinear autoregressive network with exogenous inputs (NARX).

I. INTRODUCTION

The overdevelopment of urban area has decreased the city's ground permeability and increased its surface runoff. Due climate change urban flood control is a crucial and challenging task, particularly in developed cities. Urban flood is more divesting due to fatal thunderstorm, hailstorm and cloud bursting occur both on urbanized surfaces and in small urban creeks, which deliver mass water to cities, results in flashy flood. In Maharashtra regions near Koyna and Krishna basins affect more, when large amount of water is withdrawn from both the dam. To mitigate future flood damages, it is imperative to construct an on-line accurate model to forecast inundation levels during flood periods and help people to evacuate the place before devastation.

To suggest flood disaster integrated plan model in study region the plan modeling can be done using different dataset. Disaster management for applied study on geographical point of view with related Geoinformatics approach. In the region near Krishna and Koyana basin's used special technology to collect, store, combine, analyses and overlay large amounts of information and spatial data related to locations. Collected information basis to make the integrated flood control management program and analysis in order to make the best possible way to control flood water to the repeated flood affected region in Study area. In response to the flood threat to residents and property, the Maharashtra Government has long-term endeavored in developing flood control-related infrastructures, such as enhancing sewerage systems, and urban inundations have been significantly mitigated and controlled in recent years.

ANNs[17] are used to make water level forecasts for representing the behavior of the rainfall-sewer flow processes in storm events. ANNs is type of Artificial Intelligence AI is more adaptive and efficient than traditional method like fuzzy ontology and rule based model.

The proposed model is expected to provide sufficient response time for warming up the pumps in advance for enhancing secure pumping operations and urban flood control management.

II. RELATED WORK

To provide the solution for the above problem there are different methodologies suggested by various people we are going to discuss some of them below.

D. Biondi, D.L. De [2]proposed a performance assessment of a Bayesian Forecasting system for flood forecasting that evaluates a number of flood events, the performance of a Bayesian Forecasting System (BFS), with the aim of evaluating total uncertainty in real-time flood forecasting.The performance assessment of the BFS was performed with adequate verification tools suited for probabilistic forecasts of continuous variables such as streamflow. Graphical tools and scalar metrics were used to evaluate several attributes of the forecast quality of the entire time-varying predictive distributions: calibration, sharpness, accuracy, and continuous ranked probability score (CRPS). Nien-Sheng Hsu ,Chien-Lin Huang , Chih-Chiang Wei [3]study applies an Adaptive Network-based Fuzzy Inference System (ANFIS) and a Real-Time Recurrent Neural Network (RTRLNN) with an optimized reservoir release hydrograph using Mixed Integer Linear Programming (MILP) from historical typhoon events to develop a multi-phase intelligent. The models are then constructed with either three phase modules (ANFIS-3P and RTRLNN-3P) or two phase(Stage I + II and Stage III) modules (ANFIS-2P and RTRLNN-2P).

Partly motivated by the above work Javier García-Pintado , David C. Mason , Sarah L. Dance , Hannah L. Cloke , Jeff C. Neal ,Jim FreerPaul D. Bates, Irene Kotsia et al.[4] proposed novel approach of Satellite-supported flood forecasting in river networks. Satellite-based (e.g., Synthetic Aperture Radar [SAR]) water level observations (WLOs) of the floodplain can be sequentially assimilated into a hydrodynamic model to decrease forecast uncertainty. This has the potential to keep the forecast on track, so providing an Earth Observation (EO) based flood forecast system.

Youngmin Seo ,Sungwon Kim, Ozgur Kisi, Vijay P. Singh[6] proposes water level forecasting using wavelet decomposition and artificial intelligence techniques. The objective of their proposed system is to develop and apply two hybrid models for daily water level forecasting and investigate their accuracy. These two hybrid models are wavelet-based artificial neural network (WANN) and wavelet-based adaptive neuro-fuzzy inference system (WANFIS). Wavelet decomposition is employed to decompose an input time series into approximation and detail components. The decomposed time series are used as inputs to artificial neural networks (ANN) and adaptive neuro-fuzzy inference system (ANFIS) for WANN and WANFIS models, respectively. Based on statistical performance indexes, the WANN and WANFIS models are found to produce better efficiency than the ANN and ANFIS models. WANFIS7-sym10 yields the best performance among all other models. It is found that wavelet decomposition improves the accuracy of ANN and ANFIS. As shown above all method requires large amount of data which will be in tabular format to test this data we use Gama testing.

III. METHODOLOGY

From above all discussion we can conclude that the more effective way to predict the flood is suggested by Fi-John Chang, Pin-An Chen, Ying-Ray Lu, Eric Huang and Kai-Yao Chang[1].We have make some changes in the method proposed by author as per our geographical requirement. In this proposed work, various ANNs are used to make water level forecasts for representing the behavior of the rainfall-sewer flow processes in storm events. Flood levels can be forecasted on the following data.

i) Rainfall data collected from koyana river basin.

ii) Previous water levels and rainfall ratio.

iii) A combination of both data sets

This approach adopt three ANNs coupled with statistical techniques to construct real time multi-step-ahead FSP forecast models. The flowchart of the proposed system is shown in figure 1.

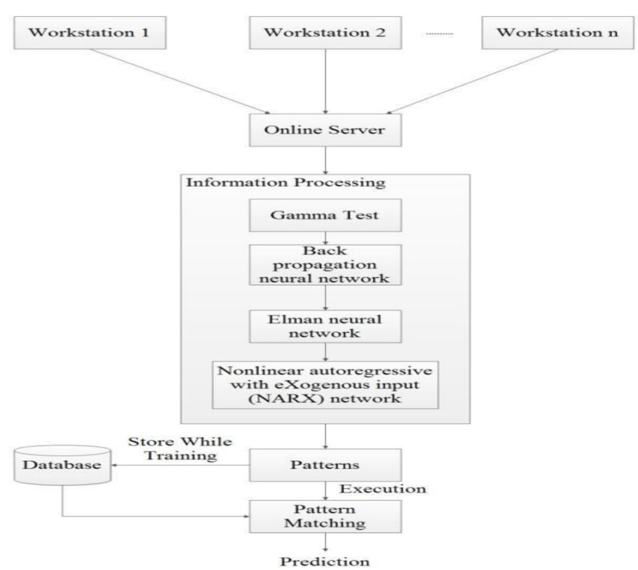

Figure 1. Water level forecasting system

In this proposed forecasting system, data are gather from stations and collected to server. The time span of rainfall affecting the rise of FSP water level is first determined by the correlation analysis. Second step is the Gamma test[12] which is applied to extracting effective rainfall factors from all possible rainfall related input combinations. Three neural network one is static BPNN[11] and two dynamic Elman NN[16] and NARX network[13][14][15] are proposed to construct multi-step-ahead FSP water level forecasts for two scenarios i.e. with a and without current FSP water level information. Finally, these constructed ANN models[1] are evaluated by performance criteria. In Maharashtra, near Koyana and Krishna basins affects more, when large amount of inflow of water to the dam and outflow of water from the dam. Need of the Model construction because of, when water level of the dam increases at that time large amount of outflow of water from the dam increases. Due to this, water level of Krishna and Koyana basins are increases and flood occurs. This system is helpful for the victims, who lose there homes, land, personal property, physical injury and agriculture damage in the flood. So this system is helpful for human beings in economical, geographical, social point of view.The proposed system consists following modules:

Step 1.Gamma Test:

- ANN required good quality of data our data is transmitted throw network in large size so there is possibility of noise in data.
- Use gamma test[12] on the input data to remove this noise and get good quality of data.

Step 2.Back propagation neural network:

- The BPNN[11] is one of the most popular ANNs . It belongs to a typical three-layered static feed forward neural network, which is comprised of multiple elements including nodes and weight connections (W and V) that link nodes. The network is divided into an input layer, a hidden layer and an output layer.
- In this study, BPNN[11] is trained by the Liebenberg–Marquardt back propagation algorithm based on the model output and observed data, and the transfer functions of hidden and output layers are of sigmoid and linear types, respectively.

Step 3.Elman neural network (Elman NN):

- The Elman NN[16] is a three-layer RNN with internal time-delay feedback connections in the hidden layer.
- It is like flip-flop which gives output depending on input as well as previous state of network .In this, defining how many previous output should consider with current input data.

Step 4.Nonlinear autoregressive with exogenous input (NARX) network:

- The NARX[13][14][15] network is a recurrent network, which is suitable for time series prediction.
- The NARX[13][14][15] network consists of three layers and produces recurrent connections from the outputs, which may delay several unit times to form new inputs.

IV. EXPECTED OUTCOME OF THE SYSTEM

Input data contains,

1. Rainfall Data, Water Level Data, Gate Opening Operation Schedule Data, Inflow-Outflow of Water data of Koyana and Krishna Basins is collected from Koyana Dam Maintenance Division Koyananagar.
2. Water Inflow Data, Water Level Data of the Krishna Basin is collected from Sangli Irrigation Department.

Depending on this data our system will conclude the expected water level at Irwin Bridge Sangli for next 48 hours.

V. CONCLUSION

In this Proposed work, three ANN are developed to make forecasts on the evolution of water level at floodwater catchment area as afunction of current catchment aera water level and rainfall information based on the inputs extracted by advanced factor selection method to forecasts inundation levels during flood periods and help people to evacuate the place before devastation.

VI. REFERENCES

[01] Fi-John Chang, Pin-An Chen, Ying-Ray Lu, Eric Huang, Kai-Yao Chang, “Real-time multi-step-ahead water level forecasting by recurrent neural networks for urban flood control”,Journal of Hydrology517 (2014) 836–846.

[02] D. Biondi, D.L. De Luca,“Performance assessment of a Bayesian Forecasting System (BFS) for real-time flood forecasting”,Journal of Hydrology 479 (2013) 51–63.

[03] Nien-Sheng Hsu, Chien-Lin Huang, Chih-Chiang Wei,”Multi-phase intelligent decision model for reservoir real-time floodcontrol during typhoons”,Journal of Hydrology 522 (2015) 11–34. [04] García-Pintado , David C. Mason , Sarah L. Dance , Hannah L. Cloke , Jeff C. Neal ,Jim FreerPaul D. Bates, Irene Kotsia et al, “Satellite-supported flood forecasting in river networks: A real case study”, Journal of Hydrology 523 (2015) 706–724.

[05] Lu Chen, Yongchuan Zhan, Jianzhong Zhou, Vijay P. Singh ,ShenglianGuo ,Junhong Zhang,“Real-time error correction method combined with combination flood forecasting technique for improving the accuracy of flood forecasting,”Journal of Hydrology 521 (2015) 157–169.

[06] YoungminSeo , Sungwon Kim, Ozgur Kisi, Vijay P. Singh,"Daily water level forecasting using wavelet decompositionand artificial intelligence techniques", Journal of Hydrology 520 (2015) 224–243.

[07] Anil Kumar Lohani, N.K. Goel, K.K.S. Bhatia,"Improving real time flood forecasting using fuzzy inference system",Journal of Hydrology 509 (2014) 25–41.

[08] Seong Jin Noh, OldrˇichRakovec, Albrecht H.Weerts, YasutoTachikawa, "On noise specification in data assimilation schemes for improved flood forecasting using distributed hydrological models",Journal of Hydrology 519 (2014) 2707– 2721.

[9] Yuan Li, DongryeolRyu, Andrew W. Western, Q.J. Wang, David E. Robertson,Wade T. Crow"An integrated error parameter estimation and lag-aware data assimilation scheme for real-time flood forecasting," Journal of Hydrology 519 (2014) 2722–2736.

[10] Tsun-Hua Yang, Sheng-Chi Yang, Jui-Yi Ho, Gwo-Fong Lin , Gong-Do Hwang, Cheng-Shang Lee, "Flash flood warnings using the ensemble precipitation forecasting technique: A case study on forecasting floods in Taiwan caused by typhoons",Journal of Hydrology 520 (2015) 367– 378.

[11] Rumelhart, D.E., Hinton, G.E., Williams, R.J., 1986." Learning representations by back propagating errors", Nature 323 (6088), 533-536.

[12] Agalbjorn, S., Koncar, N., Jones, A.J.," A note on the gamma test. Neuralcomput. Appl." 5 (1997), 131-133.

[13] Chang, F.J., Chang, K.Y., Chang, L.C., "Counterpropagation fuzzy-neural networkfor city flood control system", J. Hydrol. 358 (1)(2008), 24-34.

[14] Chang, L.C., Chen, P.A., Chang, F.J.," A reinforced two-step-ahead weight adjustment technique for on-line training of recurrent neural networks. IEEE Trans. Neural Network Learn. System", 23 (8)(2012), 1269-1278.

[15] Chang, F.J., Chen, P.A., Liu, C.W., Liao, V.H.C., Liao, C.M., "Regional estimation of groundwater arsenic concentrations through systematical dynamic-neural modeling", J. Hydrol. 499 (2013), 265-274.

[16]Elman, J.L.," Finding structure in time", Cognit. Sci. 14 (1990), 179-211.

[17] Assaad, M., BonÃl', R., Cardot, H.,"Study of the behavior of a new boosting algorithm for recurrent neural networks", (2005)Lect. Notes Comput. Sci., 169-174.