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Prediction of Landslide Displacement using NARX Model

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ABSTRACT: To prevent the damages due to landslide disaster, it is must to predict the changes in landslide displacement. Landslide displacement is direct reflection of state of the landslide. Landslide displacement time series and its influential factors could reflect the history of landslide displacement of dynamic system. In this paper we presented an application of NARX neural network for landslide displacement prediction. In addition to this, paper compares the performance of Radial Basis Function (RBF) network with NARX model. Displacement could be predicted by considering and reconstructing the relationship among the triggering factors and recurrent network such as NARX can reflect relationship among variables. Recurrent network with global feedback can learn the underlying dynamics of nonstationary environment. Comparison of RBF and NARX has been performed using MSE (Minimum Square Error).

KEYWORDS: NARX neural network model; prediction of landslide displacement; back propagation learning through time

I. INTRODUCTION

Slope is a nonlinear dynamic system. There are various factors such as topography, groundwater, soil type, earthquake, rainwater are few parameters which trigger the landslide in a particular region. Landslides are the genetic type of slope and have same characteristics. Deformation of landslide can be predicted in short time by chaotic time series data recorded for any particular slope. Artificial neural network (ANN) model have an ability to recognize time series patterns and nonlinear characteristics, which gives better accuracy over the others methods, it become most popular methods in making prediction (Vaziri, 1997; Sharda, 1994; Jones, 2004; Toriman et al., 2009). Various network models have been adopted for predicting landslide, one such type of model based on RBF has been develop for prediction. In this research paper we have presented NARX neural network trained using back propagation learning algorithm using the time series data of landslide displacement which is discussed in section III for the early prediction of landslide displacement. The constructed network has been compared with the RBF network.

II. NARX NETWORK

In this paper, the architectural approach which we have proposed to deal with chaotic time series is based upon Nonlinear Autoregressive models with exogenous input, which are therefore called NARX recurrent neural networks. Recurrent network such as NARX incorporate a static multilayer perceptron or parts thereof [5]. They exhibit the nonlinear mapping capability of the multilayer perceptron. RN can have one or more hidden layers, because static MLP are often more effective than those single hidden layer. Each computation layer of a recurrent network has a feedback around it as illustrated in Fig 1. Let the vector x1(n) denote the output of hidden layer, x11(n) denote the output of the second hidden layer, and so on. Let the vector x0(n+1) denote the output of the output layer.

Then the dynamic behavior of the recurrent network, in general, in response to an input vector u(n) is described by the following system of equations:

$$x1(n+1) = \varphi 1(x1(n),$$
$$u(n))\ x11(n+1) = \varphi 11(x11(n),\ x1(n+1))$$
$$x0(n+1) = \varphi 0(x0(n),\ xK(n+1) \qquad ..\ (1)$$

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where φ1(·,·), φ11(·,·) denotes the activation functions characterizing the first hidden layer and second hidden layer, φ0(·,·) denote the activation function of output layer of RN. The recurrent network based on use of static multilayer perceptron and delay line memories, provides a method for implementing the nonlinear feedback system described by equations [5]:

$$x(n+1) = \varphi(Wax(n) + Wbu(n)) \qquad .. (2)$$

$$y(n) = Cx(n) \qquad ..(3)$$

where Wa , Wb , C and y(n) represents the synaptic weights of hidden neurons which are connected to feedback nodes in input layer, synaptic weights of hidden neurons connected to source nodes in input layer, synaptic weights of linear neurons in the output layer that are connected to hidden neurons and the output respectively. Fig 2 illustrates the architecture of NARX network implemented with feedforward network embedding with memory at input layer. A global feedback is connected to the input layer. The use of global feedback has the potential of reducing the memory requirement significantly [9]. Activation functions used in the network can be logistic function or hyperbolic tangent function.

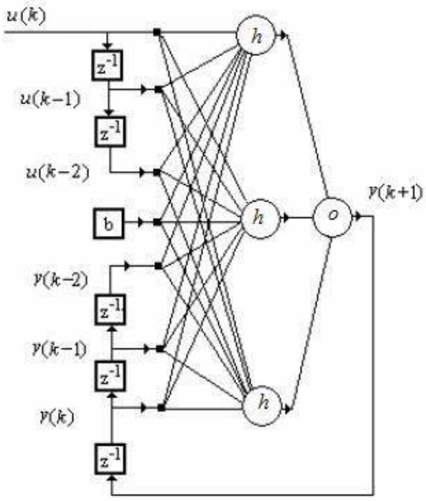

FIG2. NARX MODEL WITH DELAY AT INPUT

III. TIME SERIES PREDICTION WITH EMBEDDING MEMORY

A. *Vanishing Gradients in Recurrent Networks*

Vanishing gradient problem pertains to the training of the network to produce a desired response at the current time that depends on input data in the distant past [5]. The point is that because of the combined nonlinearities, an infinitesimal change of a temporally distant input may have almost no effect on network training. The problem may arise even if large change in the temporally distant input has an effect is not measurable by the gradient.

Several approaches have been suggested to solve the problem of vanishing gradient in training RNNs. Most of them rest on including embedding memory in neural networks, whereas several others propose improved learning algorithms, such as the extended Kalman filter algorithm, Newton type algorithm, annealing algorithm, etc. Embedded memory is particularly significant in recurrent NARX and NARMAX neural networks [8]. This embedded memory can help to speed up propagation of gradient information, and hence help to reduce the effect of vanishing gradient. There are various methods of introducing memory and temporal information into neural networks. These include creating a spatial representation of temporal pattern, putting time delays into the neurons or their connections, employing recurrent connections, using neurons with activations that sum input over time, etc [5].

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B. *Research Methodology*

Adding a time delay at the input layer of the network provides a memory to the static MLP. The static MLP accounts for the nonlinearity. NARX network has two delay memories each for input and target or feedback series. There are two modes which have a concern in training NARX network. Output of NARX network would estimate nonlinear dynamic system that we are modeling. The output is then fed back to the input of the feedforward neural network as part of the standard NARX architecture, as shown in the Fig 3.We created a series-parallel architecture by computing the output during the training of the network by providing the true output as shown in Fig 4. This provides two advantages. The first is that feedforward network input is more accurate. The second is that backpropagation can be used for training of feedforward architecture. In this paper, we have trained our network using series parallel architecture and then parallel architecture is used for the early prediction of displacement.

IV. ENGINEERING EXAMPLE

A. *Landslide Displacement Data*

The monitoring data which has been used to construct the network model is recorded from August 2003 to July 2007. 48 group time series are obtained and time interval between each record is one month. It includes seepage pressure, steel stress of central main reinforcement in the north of anti-slide pile, and displacement. The time series of six different monitoring points recorded for 48 months. The monitored data is of Hong Shi-bao landslide obtained from Institute of Water Resources and Hydropower Research. Training samples are representative of non-stationary behaviour of environment.

B. *Establishing Prediction Model*

Landslide displacement is a direct reflection of the state of the landslide. External dynamical factor such as groundwater, seepage pressure contribute majorly in displacement. Whereas other factors such as anti-slide pile can be main resistant factor of landslide displacement. Landslide is evolved under the combined effects of these factors. The impact of groundwater to landslide is characterized by seepage pressure, while the working state of anti-slide pile is represented by steel stress in anti-slide pile. This paper focuses on early prediction of displacement which occur due to the influential factors.

C. *Prediction Model*

During training, the inputs to the feed forward network are just the real/true ones – not estimated ones, and so the training process will be more accurate. Network model has been designed using MATLAB neural network toolbox. The network training function updates the weight and bias values according to Levenberg-Marquardt optimization (trainlm). In general, in function approximation problems, for networks that contain up to a few hundred weights, the LevenbergMarquardt algorithm will have the fastest convergence. Training and testing data is divided using dividerand function. The property DIVIDEMODE set to TIMESTEP means that targets are divided into training, validation and test sets according to timestamps.70% of training, 15% of validation and 15% of testing data is obtained from the total dataset of 48 group records. The Figure5 illustrates a two layer NARX network trained in seriesparallel architecture. The network contains 10 hidden neurons with logsigmoid function and a single linear out neuron. $x(t)$ and $y(t)$ represents the external inputs and target series respectively. Learning rate of 0.001 and time delay of 2 timestamps (selected heuristically).

After training on 43 time steps in open loop, the network is then closed as shown in Fig 6, for multi-step prediction. In some applications it is expected from an early prediction neural network to compute the output a time step ahead. One time delay is removed to make the network predict one time step early output. The new network returns the outputs which are shifted left one time step. For landslide displacement prediction we have used the early prediction network and calculated the error between the actual value (AV) and the predicted value (PV).

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TABLE1. TRAINING PERFORMANCE

N	Training Performance	Output	Target
43	0.0502	16.9300	16.93
44	0.0007	17.2400	17.24
45	0.0016	17.4685	17.55
46	0.0013	17.8410	17.86
47	0.0027	18.0985	18.17

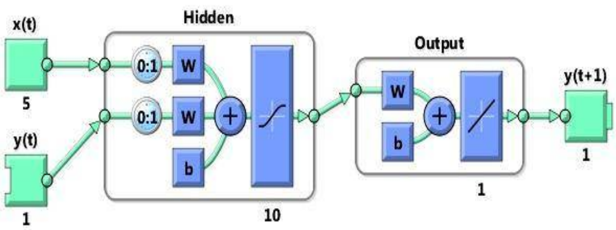

FIG7. NARX EARLY PREDICTION NETWORK

TABLE2. NARX PREDICTION ERROR

N	AV /mm	PV (t+1) /mm	MSE
44	17.24	17.24	0.0031
45	17.55	17.36	
46	17.86	17.90	
47	18.17	18.09	
48	18.37	18.37	

Table1 shows the performance of the network during training on different time steps and comparison of current value and network calculated values for that time step. After training of 43 time steps, prediction for next 5 time steps have been performed using early prediction network for (t+1) time step, i.e. one month ahead prediction of displacement. Table2 shows the results of prediction of NARX network.

D. RBF Neural Network

Radial basis function based neural network is also constructed for comparison of prediction results and for determination of efficacy of the network present in this paper. A RBF network is designed using *newrb* function which designs a RBF network starting with 0 neurons in hidden layer and at each step it increase the number of neuron by one, thereby decreasing the error value in each step. The number of hidden neurons can reach up to N, where N is the number of data points in training set. RBF model employs curve fitting in high-dimension space. Spread factor of RBF effect the prediction results. Too large a spread means a lot of neurons are required to fit a fast-changing function. Too small a spread means many neurons are required to fit a smooth function, and the network might not generalize well. RBF with N hidden neurons, where N is number of training examples, will produce zero error with design vectors, but error in testing vectors is not acceptable as compared to other networks. After training of RBF network it is tested for the prediction of next time step. Table4 shows prediction error results of RBF network. Table3 represents the MSE values achieved against number of nodes in hidden neuron. It shows that minimum error achieved is 0.006 with 27 hidden neurons and regression value of 0.996.

TABLE3. RBF NETWORK TRAINING PERFORMANCE

No. of Nodes	MSE	No. of Nodes	MSE
2	4.9123	15	0.1422
3	2.8120	16	0.1232
4	1.5778	17	0.1123
5	1.5231	18	0.0921
6	0.7031	19	0.0810
7	0.6681	20	0.0646
8	0.6624	21	0.0478
9	0.5398	22	0.0375
10	0.4085	23	0.0345
11	0.2980	24	0.0337
12	0.2242	25	0.0307
13	0.2200	26	0.0285
14	0.1660	27	0.0060

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TABLE4. RBF PREDICTION ERROR

N	AV /mm	PV /mm	MSE
44	17.24	17.2217	0.006
45	17.55	17.5358	
46	17.86	17.9841	
47	18.17	18.2891	
48	18.37	18.4638	

E. MODEL SELECTION

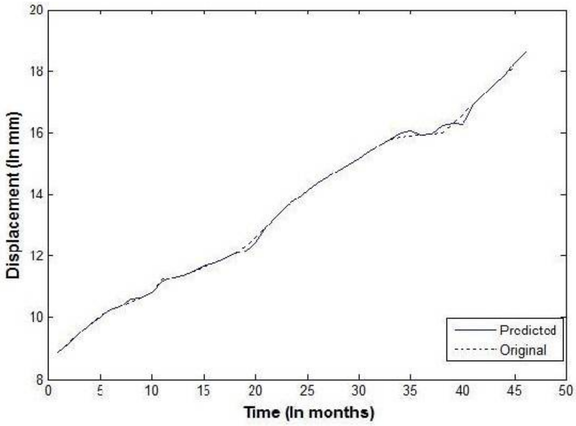

FIG 8. PREDICTION RESULTS OF NARX NETWORK

Fig 8 illustrates the predicted and original graph of displacement. Error analysis explain that NARX network have better performance. Table5 shows prediction results of two models on testing dataset.

TABLE5. PREDICTION ERRORS OF TWO MODELS ON TESTING DATASET

Network	MSE
NARX	0.0031
RBF	0.0060

V. CONCLUSIONS

The prediction of landslide displacement was related to several influencing factors and there were interactions in factors. Various Neural networks establish nonlinear relationship among those factors. NARX recurrent neural networks have the potential to capture the dynamics of nonlinear dynamic system. This affirmation has been made based on the results performed during the experiment. Fig 8 illustrates that NARX prediction of input-output mapping closely captures the nonlinear dynamic of the system.

Different architectures of recurrent networks can be used for temporal processing. The approach which we have presented in this paper has shown that minimum error is achieved through NARX for displacement prediction. The NARX model can be considered as an alternative model for prediction of landslide displacement.

VI. ACKNOWLEDGEMENT

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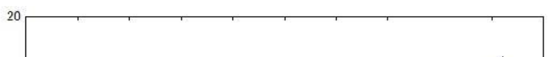

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BIOGRAPHY

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