Nonlinear System Identification Using Functional Link Multilayer Perceptron Artificial Neural Networks

Sudhansu Mishra
Birla Institute of Technology, Mesra

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[1]Kumar Gaurav, [2]Amit Kumar Sahoo, [3]Sudhansu Kumar Mishra

[1,3]Birla Institute of Technology, Mesra, India
[2]Centurion Institute of Technology, Bhubneshwar, India
Email: [1]gaurav8131@gmail.com; [2]amitkumar2687@gmail.com; [3]sudhansu.nit@gmail.com

Abstract. In this paper we have proposed a novel Functional Link Multilayer Perceptron (FLMLP) network for nonlinear system identification. The identification of nonlinear dynamic system finds wide application in stability analysis, controller design, analysis of power systems, modeling of multipath communication channels etc. The proposed model takes the advantage of nonlinearity in MLP due to multilayer and functional expansion of FLANN model. We have also proposed an efficient optimization technique named as Cat Swarm Optimization (CSO) algorithm to update the weights of FLMLP network. Identification of bench mark nonlinear dynamic system is carried out through simulation study to validate the proposed model. The simulation study reveals the proposed model provides superior identification compared to individual performance of MLP and FLANN based models

I. INTRODUCTION

Model of complex dynamic system is too difficult by using conventional numerical analysis methods. System identification is an alternative technique for the efficient modelling of these systems. The objective of identification process is to determine a suitable mathematical model of a given system. It can be useful for predicting the behavior of the system under different operating conditions. A mathematical model is very useful as well as very compact way, of describing the knowledge about a process or system. There are basically two ways of determining a mathematical model of a system (i) implementing known laws of nature or (ii) through experimentation on the process. The applications of direct modelling or system identification are in areas of control system engineering, process control, power system engineering, image and speech processing, geophysics, vibration control and biomedical engineering.

Many authors have works on identification by using multilayer perceptron (MLP) [1,2]. Later on some other -authors have develop Functional link Artificial neural network (FLANN) structure to eliminate the difficulty due to multilayer to get non-linearity, and it results in better performance and low complexity. In this paper, we proposed FLMLP structure is best suited for identification of complex time varying nonlinear dynamic system with higher accuracy. The proposed structure incorporates advantages of both MLP and FLANN based models.

The conventional algorithm is used to find best feasible parameter of the system at minimal cost function, where it is very challenging to achieve the proper model. All these models use gradient search algorithms such as the Least mean square (LMS), Recursive least square (RLS), Back Propagation (BP) etc. The main disadvantage of these algorithms is that, they may be trapped in local optimal point. To avoid this shortcoming, researchers have applied heuristic based approaches, such as the Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Bacterial forging optimization (BFO), Artificial Immune System (AIS), Clonal Particle Swarm Optimization (CPSO) etc. for training the neural network [3-15]. All these heuristic techniques have been applied to different interesting fields of applications in the last few decades. In this paper, we have proposed similar swarm intelligence based algorithm named as Cat Swarm Optimization (CSO) algorithm. The results demonstrate superior identification performance of the new network as compared to that achieved by either FLANN or MLP based networks.

The paper is organized as follow: Section II introduces the adaptive identification problem. Section III deals with proposed FLMLP network architecture for system identification. The basic principle and algorithm required for identification of nonlinear system is dealt in section IV. To validate the performance of the proposed model, the identification of standard nonlinear dynamic system is carried out through simulation and is presented in section V. Finally, the conclusion of the whole paper is outlined in section VI.

II. PROPOSED FLMLP NETWORK FOR SYSTEM IDENTIFICATION

System Identification is the route to build a mathematical model for the anonymous system by monitoring its input-output data. Identification consists of two parts: the selection of an appropriate identification model and an estimation of model's parameters. The goal of the identification problem is to raise a relevant model that can generate an output $\hat{Y}$ which can approximate the plant output Y for the same input X, in such a way that the mean square error is the least.

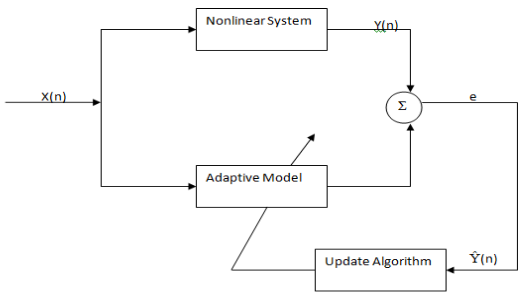

Fig.1. Block Diagram of System Identification

2.1 Multilayer Perceptron

The MLP is a multilayer architecture with one or more hidden layers between its input and output layers. The inputs to any layer consist only of outputs of the preceding layers through a set of weights. Except the input layer, all the nodes in all layers of MLP contains a tanh( ) function. The output of the nodes of the input layer is the input pattern applied. The weighted sum of outputs of a lower layer is passed through the nonlinear function of a node in the upper layer to produce its output. Hence, in this architecture, the outputs of all the nodes of the network are computed. A comparison is made between the outputs of final layer to the target pattern associated with the input pattern. The error between the target node and output layer node is considered for updation of weights of the network. The Back Propagation algorithm attempts to minimize the mean square error or cost function by updating all thee weights of the network.

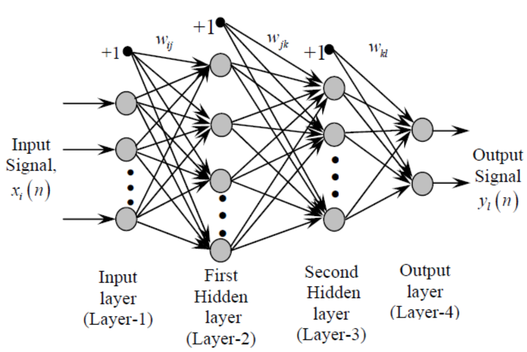

Fig 2. Structure of Multilayer Perceptron

2.2 Functional Link Artificial Neural Network

The FLANN initially proposed by Pao is a single layer ANN in which the input gets functionally expanded. The major difference between hardware structures of FLANN and MLP is that FLANN has only input and output layers and the hidden layers are completely replaced by nonlinear mappings. The task performed by hidden layers in an MLP is carried out by functional expansions in FLANN. Hence, the need of hidden layer is removed. It can generate nonlinear decision boundaries and hence, is capable of forming complex decision boundaries. The functional link acts on an element or the entire pattern itself by generating a set of linearly independent functions.

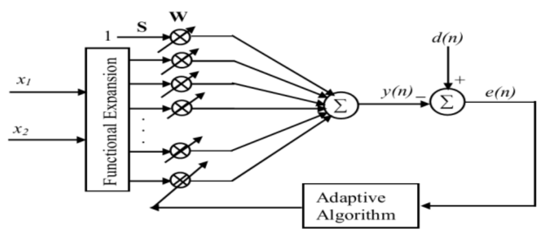

Fig 3. Structure of FLANN

2.3 Proposed Functional Link Multilayer Perceptron (FLMLP) Network

The proposed FLMLP network is a combined form of Functional link artificial neural network and Multilayer Perceptron. The complete structure of FLMLP is shown in the figure. It shows that the input is expanded using trigonometric expansion like the FLANN structure. There is a hidden layer like MLP in the proposed structure. Hence, the network became nonlinear due to functional expansion of the input and presence of multiple layer. Hence, it takes the advantage of both MLP and FLANN to achieve the non-linearity to solve the non-linear problem. The trigonometric expansion transforms the linearly non separable problems in original low dimensional signal space into separable one in a high dimensional space.

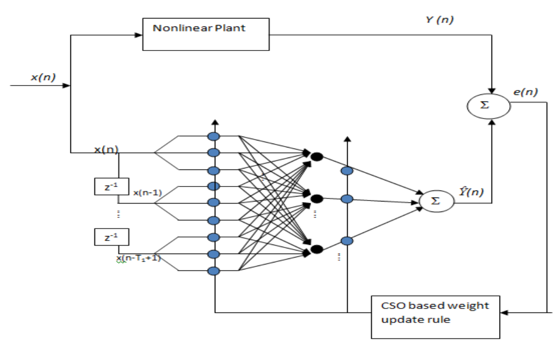

Fig 4. Structure of Proposed FLMLP network

III. PROPOSED WEIGHT UPDATION USING CAT SWARM OPTIMIZATION (CSO) ALGORITHM

Chu and Tsai introduced an evolutionary algorithm which imitates the natural behavior of cats [16]. According to this algorithm, the cats possess a strong curiosity and hunting skills towards their target. When they sense the target, they quickly chase them spending large amount of energy otherwise most of the time they remain in rest condition. These two characteristics (resting with slow movement and chasing with high energy) are represented by seeking and tracing mode respectively. The seeking mode corresponds to a global search technique in the optimization problem, whereas the tracing mode corresponds to a local search technique.

According to CSO algorithm, the behavior of cats is being customized as follows:

$$V_{id} = w*V_{id} + c*r*({}_{gd} - Xid) \quad (1)$$

$$X_{id} = X_{id} + V_{id} \quad (2)$$

where w is inertia weight, c is the acceleration constant and r is a random number uniformly distributed in range [0,1], d represents the dimension, P_{gd} is the global best position.

3.1 Algorithm of CSO

Two groups of cat i.e. one group containing cats in seeking mode and other group containing cats in tracing mode is used to find the optimal solution using CSO algorithm. These two groups combine to solve the optimization problem. A mixture ratio (MR) is used which may be defined as the ratio of number of cats in tracing mode to the number of cats in seeking mode.

Step - 1: Initialization of random position of cats in D-dimensional space (X_{id})

Step - 2: Initialization of random velocity for cats as V_{id} .

Step - 3: The fitness of each cat should be evaluated and the position of the cat with best fitness should be stored as P_{gm} where m=1, 2....…. D.

Step - 4: Cats are randomly picked from the population ratio according to mixture ratio. Their flag are now set to their seeking mode. For rest of the cats, the flag is set to tracing mode.

Step - 5: If the flag of the ith cat is seeking mode, apply it to the seeking mode process, otherwise apply it to the tracing mode process. Their corresponding modes are now followed.

Step - 6: The fitness of each cat is evaluated and the position of the cat with best fitness is stored as P_{im} where m=1, 2…… D.

Step - 7: The fitness of P_g and P_l is compared and then P_g is updated.

Step - 8: Check the termination condition, if satisfied, terminate the program otherwise repeat Steps 4-7.

IV. SIMULATION RESULTS

To demonstrate the performance of the proposed identification model simulation study using MATLAB is carried out. The block diagram of above fig.1 is simulated where the connecting weights and co-efficient of the MLP-FLANN model is updated using CSO.

The following nonlinear models has been used in the simulation study:

Example-1: $f_1(x) = x^3 + 0.3x^2 - 0.4x$

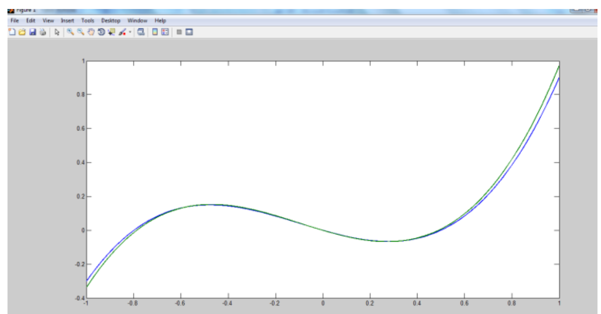

Fig5. Simulation result of Example1

Example-2:

Identification of non-linear system is carried out through simulation, and updating the weights of a non-linear system identification model by using FLANN and FLMLP based models. The difference equation of the plant is

$$\frac{Y(z)}{X(z)} = 0.26 + 0.93z^{-1} + 0.26z^{-2} = H(z)$$

$$y(n) = 0.26x(n) + 0.93x(n-1) + 0.26x(n-2)$$

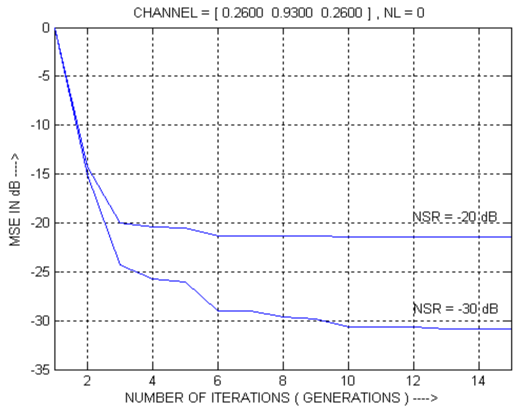

Fig6. Mean square error plot

At the time of training, we observed that the NSR during the identification has comparatively reduced than other method with random input. Again, it is observed that the proposed MLP-FLANN based model converges faster and lower NSR than only FLANN based model.

So one can clearly observe from the above simulation result that the CSO out performs the GA and PSO. Also it indicates that the CPU time taken by CSO is better compare to GA and PSO.

V. CONCLUSION

A novel FLMLP based model has been proposed for successful identification of nonlinear systems. The above identification technique takes advantage of both MLP and FLANN structures to solve this interesting and challenging problem. An efficient technique, swarm intelligence based optimization, named as Cat Swarm Optimization algorithm has been successfully implemented for updating the weights of the proposed model. The performances of the proposed model has been evaluated and compared, using mean square error plot. The simulation study reveals that the proposed algorithm gives better result as compared to other two competitive structures i.e. MLP and FLANN. Further study in this field may include the evaluation of the proposed model to some other real time systems. The aforesaid network can also be expanded for inverse modeling.

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