Application of a Rapid Neural Network for Identification of a Micro-Machine System

Omar H. Abdalla
Refaat S. Ahmed

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APPLICATION OF A RAPID NEURAL NETWORK FOR IDENTIFICATION OF A MICRO-MACHINE SYSTEM

Refaat S. Ahmed and Omar H. Abdalla
Electrical Engineering Dept., Helwan University, Cairo, Egypt.

Abstract
This paper describes the application of a rapid neural network for identification of a micro-machine system from the experimental input-output data. The advantage of the rapid learning algorithm is that it does not need repetitive iterations as most learning algorithms. It is capable of achieving a good solution in one training scan. Identification accuracy is assessed by direct comparison between the actual output of the system and the output of the neural network identifier.

The results of the rapid neural network are compared with the results of the conventional feedforward neural network with back-propagation learning algorithm. The results show excellent performance of the rapid neural network for an input/output model identification of the micro-machine system from experimental data.

1 Introduction
The major difficulty in providing adequate power system control is the fact that these systems are multi-input multi-output (MIMO), nonlinear and their dynamic models are very complex. Accurate modeling of a system is most important in assessment and prediction of performance and control design. Neural network can provide a powerful method for modeling highly nonlinear processes without the need for a mathematical model. It has already been applied extensively to various applications such as identification and control of nonlinear dynamic systems [1-4]. Neural networks can be viewed as nonlinear dynamic mapping of control inputs onto observation outputs. One of the most common used neural networks in the area of system identification and control is the feed-forward multi-layer neural network (MNN) [5-7]. The back-propagation learning algorithm is the most common one for training neural networks [5-7]. It uses gradient descent method to provide a suitable solution for neural network weights by minimizing the sum of squared errors. Training is usually done by iterative updating of the weights according to the error signal. The training may take long time and convergence behavior may vary depending on the learning rate chosen, the number of hidden neurons and nature of the training patterns. Back-propagation learning algorithm is often too slow for practical applications.

In this paper, a rapid neural network is used for identification of the micro-machine system from the experimental input-output data. For off-line training, the proposed neural network and its learning algorithm is capable achieving a solution in one training scan (one shot) as opposed to the most iterative training algorithms [8].

2 System Description
The system configuration is shown in Fig. 1. Briefly it comprises of a 3 kVA micro-synchronous-generator connected to the laboratory busbar via a transmission line simulator [9]. An analogue simulator represents a three-stage steam turbine with a single re heater and electro-hydraulic governor and interceptor valves. The experimental data for the system identification have been obtained from the computer controlled micro-machine system [9].
Consider a single layer neural network with \( n \) input neurons and \( m \) output neurons. Assume \( A \) is \((p \times n)\) matrix of the input patterns and \( Y \) is \((p \times m)\) matrix of the desired output patterns of the training data set. Where \( p \) is the number of patterns, \( n \) is the dimension of the input patterns (\( n < p \)) and \( m \) is the dimension of the output patterns. The function of the \( j^{th} \) output neuron in a neural network can be described as: \( o_j = \sigma(\sum w_{ij} x_i) \). Where \( o_j \) is the output of the \( j^{th} \) neuron, \( x_i \) is the \( i^{th} \) input, \( w_{ij} \) is the weight between the \( j^{th} \) output neuron and the \( i^{th} \) input node, and \( \sigma \) is a nonlinear activation function \( \sigma(x) = (e^x - e^{-x})/(e^x + e^{-x}) \). The network output in a matrix form is given by \( Y = AW \), where \( W \) is weight matrix of the neural network. The system of equations \( Y = AW \) is a nonlinear due to the nonlinear computation of the output neurons. If a matrix \( B \) is obtained by applying \( \sigma^{-1} \) to each element of \( Y \), the system of equations \( B = AW \) will be a linear system.

**Theorem [6]:**

The system of equation \( AW = B \) has a solution if and only if rank \((A) = \text{rank} (A_{\text{aug}}) \) and has a unique solution if and only if rank \((A) = \text{rank} (A_{\text{aug}}) = n \). Where \( A_{\text{aug}} = [A|B] \) is the augmented matrix.

The purpose of the supervised learning of the neural network is to find a weight matrix, \( W \), which satisfies the solution of the system equations \( AW = B \). In order to have a solution for the weight matrix, the condition of the above theorem must be satisfied. If the condition is satisfied, then the training set can be implemented via a single-layer neural network. For most problems, the above condition cannot be satisfied. Increases the dimension, \( n \), of the input data matrix by adding additional linearly independent columns may satisfy the rank condition.

Adding additional linearly independent columns to the input matrix, \( A \), means adding hidden neurons to the network (multi-layer neural network). Assume that \( V \) is the weight matrix from the input to the hidden neurons, and \( A_{\text{add}} \) is \((nxh)\) matrix represents the additional linearly independent columns, \( A_{\text{add}} = [\sigma(AV)] \). The newly formed matrix is denoted as \( A_{\text{new}} = [A|A_{\text{add}}] \), then the rank of the matrix \( A \) is increased by \( h \) (hidden neurons). For suitable choice of the hidden neurons, the rank \((A_{\text{new}}) = \text{rank} (A_{\text{new}} | B) \), then a solution, \( W \), can be found.

Connection weights between the original \( n \) input neurons to the additional \( h \) hidden neurons are made. These weights form the matrix \( V \) with \((nxh)\) dimension. The output of the \( n \) input neurons and the \( h \) hidden neurons directly connected to the \( m \) output neurons forms the weight matrix \( W \) with \(((n+h)xm)\) dimension. The architecture of the neural network is shown in Fig. 2.
4 Learning Algorithm

The problem of determining \( W \) can be formulated as linear least square problem. The rapid learning algorithm is given below:

1. Given the input pattern matrix, \( A \), and the pattern matrix of the desired output, \( Y \), of a training data set.
2. Calculate the matrix \( B = \sigma^{-1}(Y) \).
3. Add \( h \) hidden nodes and assign random weights to it.
4. Solve the weight matrix, \( W \), by minimizing \( |A_{\text{new}}W - B|_2^2 \) by the least square method.
5. If the mean square error is not satisfied, add additional hidden neurons and go to step (4); otherwise, stop.

5 System Identification

The micro-machine system is a MIMO (2-inputs and 3-outputs) system [8]. The system inputs are the governor input, \( U_g \) and the exciter input, \( U_{ex} \). The system outputs are selected to be the rotor speed deviation, \( \delta \), terminal power, \( P_t \), and the terminal voltage \( V_t \). These are the principal generator quantities to controlled, and are readily accessible for measurements. A sequence of random step signals was imposed on the turbine governor and generator exciter inputs, in order to produce data for modeling. The random input signals are shown in Fig. 3. A data set consists of 400 input-output patterns are collected with a sampling interval of 20 ms.

The task of system identification is essentially to find suitable mappings which can approximate the mappings implied in a dynamic system. There are two identification structures: parallel structure and series parallel structure [2]. In this paper, the series parallel structure is used. In series parallel structure, the input to the system and the past values of the system outputs form the input to the neural network identifier.

6 Results

Two different schemes of neural network are used to identify the micro-machine system. In the first scheme, three separate neural networks are used to identify the system outputs as shown in Fig. 4. Each neural network consists of 3 input nodes, 5 hidden neurons, and one output neuron and is used to identify only one output from the system outputs. The input vectors to the first, second and third network are \([U_g(k), U_{ex}(k), \delta(k-1)]\), \([U_g(k), U_{ex}(k)]\), and \([U_g(k), U_{ex}(k), P_t(k-1)]\) respectively. The outputs from these networks are \( \delta(k) \), \( V_t(k) \), and \( P_t(k) \) respectively.

In the second scheme, only one neural network is used to identify all the outputs of the micro-machine system as shown in Fig. 5. The network consists of 5 input nodes \([U_g(k), U_{ex}(k), \delta(k-1), V_t(k-1), P_t(k-1)]\), 20 hidden neurons, and 3 output neurons \([\delta(k), V_t(k), P_t(k)]\). For limited space the result of the second scheme only is listed.

Figure 6 shows a direct comparison between the actual system outputs and the neural network outputs. The neural network outputs are very close to the actual system outputs. For purpose of comparison, a feedforward neural network (5 input nodes, 20 hidden neurons and 3 output neurons) with the back-propagation learning algorithm is used for the system identification. The system and neural network outputs are shown in Fig. 7. The results show excellent performance of the rapid neural network for identification of the micro-machine system.
7 Conclusions

The paper presents the application of a rapid neural network for identification of a micro-machine system from the experimental input/output data. For off-line training, the proposed neural network and its learning algorithm is able to achieve a solution in one training scan (one shot) as opposed to the most iterative training algorithms. It does not need iterative training as in well-known back-propagation learning algorithm.

The accuracy of the neural network identifier is assessed by direct comparison between its outputs and the actual system outputs for the same inputs. The results of the proposed neural network are compared with the feedforward neural network with back-propagation learning algorithm. The results show that a very close agreement between the proposed neural network and the system outputs, which reveal that the rapid neural network is very effective for identification of the micro-machine system.

References


Fig. 5. System and neural network outputs.
(One-time training neural network)
Fig. 6. System and neural network outputs
(Back-propagation learning algorithm)